



LMDE
LEADING AND MANAGING
IN THE DIGITAL ERA



LMDE 2025 CONFERENCE

Leading & Managing in the Digital Era:
SHAPING THE FUTURE WITH
AI AND DATA ANALYTICS

Proceedings of Extended Abstracts



ΟΙΚΟΝΟΜΙΚΟ
ΠΑΝΕΠΙΣΤΗΜΙΟ
ΑΘΗΝΩΝ



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OF ECONOMICS
AND BUSINESS



JUNE 13 - 17, ATHENS, SYROS | GREECE

**Gregory Prastacos, Ioannis Ntzoufras, Dimitris Karlis,
Xenia Mamakou, Vasilis Chasiotis**

Editors

LMDE 2025 CONFERENCE

Leading & Managing in the Digital Era:
Shaping the Future of Work
and Business Education

**Proceedings of
Extended Abstracts**

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PREFACE

Artificial intelligence, machine learning, data analytics, and so many other digital technologies are transforming the very fabric of management and business education. They create an environment where best practices require that humans work with machines to effectively respond to market dynamics and customer needs and anticipate future trends. They also create a new set of ethics and governance issues.

As organizations embrace these technologies, management roles are drastically changing, and leaders are no longer just visionaries; they become *data-driven* strategists who embrace agility, adaptability, and a deep understanding of technology's potential. They use technology-driven insights to foster innovation and drive sustainable growth. Communication is becoming more instantaneous and data-centric, enabling organizations to foster deeper connections with their stakeholders, facilitate collaboration and enhance overall performance. This creates the risk of a personal communication, and challenges leaders to find ways to foster organizational belonging and culture. Moreover, the rise of digital technologies is creating unprecedented opportunities for entrepreneurs. Startups can harness AI and data analytics to automate and scale operations, enhance customer experiences, and disrupt industries with innovative solutions.

The impact of these advancements extends beyond the corporate environment, reshaping the nature of business education. Educational institutions are reimagining curricula to equip future leaders with the skills needed to navigate this digital era. Business schools are now focusing on interdisciplinary approaches that blend traditional management principles with technological acumen, preparing students for the complexities of modern entrepreneurship. The future of education lies in cultivating a mindset of continuous learning and adaptation, ensuring graduates are not only ready to lead but also to innovate in a world where the cumulative effects of change disrupt traditional practices every decade. By embracing AI and related developments, we can transform the way we work, live, and govern, paving the way for a more dynamic and inclusive future.

The 2nd Leading and Managing in the Digital Era (LMDE) conference explores these exciting possibilities and provides directions on how to shape the leaders of tomorrow. This book includes the abstracts of the papers presented in the conference. The book is organized according to the sessions of the conference and covers an interdisciplinary range of topics whose common thread is AI and data analytics in four main conference tracks: Leadership, Governance and AI; AI and Data Analytics for Improved Operations; Strategy, Innovation and Entrepreneurship in the AI Era; and Transforming Business Education and Research for the AI Era.

On behalf of the Steering Committee, I would like to thank the authors for submitting their papers to the conference, the reviewers who reviewed the submissions, and the leadership of The Athens University of Economics and Business, of Stevens Institute of Technology, and of the Bodossaki Foundation for their support. I specially would like to thank the members of the organizing committee who worked innumerable hours to bring this conference to fruition: Xenia Mamakou (AUEB) who was the point of reference of the conference and took care of all the logistics; Ioannis Ntzoufras (AUEB), chair of the program committee; Dimitris Karlis (AUEB) chair of the organizing committee; Vasilis Chasiotis (AUEB) who took care of the production of the book of abstracts; Emily Nguyen (Stevens) who took care

of all the artistic work and of the production of flyers, and Ian Reitz (Stevens) who took care of all the communication and promotion of the conference. Finally, many thanks to our sponsors for their generous support.

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- **Michael zur Muehlen**, Associate Professor of Information Systems, Associate Dean, Stevens Institute of Technology, USA

KEYNOTE SPEAKERS

IT TAKES TWO TO THINKLET: ADAPTING COLLABORATION ENGINEERING FOR HUMAN-AI PARTNERSHIPS

GJ de Vreede

Dean, School of Business, Stevens Institute of Technology, USA

Description: The emergence of sophisticated generative AI has fundamentally transformed the landscape of collaborative work. No longer confined to the role of passive tools, modern AI systems now function as autonomous agents capable of meaningful participation in teamwork. From co-authoring documents to contributing creative ideas and making decisions, these AI systems are increasingly becoming active teammates in collaborative scenarios. This evolution signals a shift from AI as productivity software to AI as collaborative partners with unique capabilities to augment collaborative work.

For over two decades, the field of Collaboration Engineering has developed rigorous approaches to designing and deploying repeatable collaboration processes for high-value organizational tasks. Collaboration Engineering has introduced the concept of "thinkLets" – modular, reusable building blocks that encapsulate facilitation expertise and enable predictable patterns of collaboration. Through careful sequencing of thinkLets, organizations can create sustainable collaborative work practices that deliver consistent value without requiring professional facilitators.

However, the existing Collaboration Engineering approach and concepts were conceived exclusively for human teams. Its foundational assumptions, design methodologies, and implementation approaches were developed with human cognitive capabilities, social dynamics, and communication practices in mind. The theories, models, and practices that have proven effective for human collaboration are not necessarily directly applicable to teams where one or more members is an AI. The asymmetric capabilities between human and AI participants, unique interaction challenges, and novel team dynamics create a fundamentally different collaborative environment requiring rethinking of our established approaches to design collaboration processes and techniques. This keynote addresses the critical question: How must Collaboration Engineering evolve to accommodate and leverage AI teammates in collaborative processes? What adaptations to its core concepts, design methodologies, and implementation strategies are necessary to create effective, sustainable Human-AI collaboration processes?

Drawing on insights from both Collaboration Engineering research and recent advances in AI capabilities, I will present several key adaptations required for this new frontier. These include modifications to the thinkLet concept to accommodate AI-specific roles and interaction patterns, extensions to process design methodologies that account for AI capabilities and limitations, and new approaches to facilitate knowledge transfer to practitioners leading Human-AI teams. Additionally, I will outline a research agenda organized around the Ways Framework (Thinking, Working, Modeling, Supporting, and Controlling) to guide future investigation in this emerging field. This agenda identifies research questions whose answers will help organizations successfully integrate AI teammates into their collaborative work practices.

As AI continues to evolve from tools to powerful teammates, Collaboration Engineering must similarly evolve to provide theoretically-grounded, practically-applicable approaches to designing effective hybrid collaborative processes. This presentation aims to lay the foundation for this essential adaptation, ensuring that the valuable insights from decades of collaboration research can be effectively applied to our new reality of Human-AI teamwork.

STATISTICAL NETWORK ANALYSIS: CHALLENGES AND OPPORTUNITIES

Nial Friel

Professor of Statistics, University College Dublin, Italy

Description: Network data are found everywhere. A network can be conveniently thought of as a collection of nodes connected by edges. A node could be, for example, a business, an industry or even a country. And an edge could represent any relationship between any two nodes, for example, the amount of trade which flows from one business to another. Analysing and understanding the complex patterns that can arise in networks presents both a challenge, but also an opportunity to gain insights, otherwise undiscovered. I will aim to highlight these aspects through a collection of diverse case studies.

DEALING WITH POWERFUL, RAPID TECHNOLOGICAL TRANSFORMATION: SHAPING A NEW ERA FOR BUSINESS SCHOOLS AND INDUSTRY PARTNERSHIPS

Paulo Goes

Dean of the Freeman School of Business, Tulane University, USA

Description: AI is the latest and most powerful technological transformation wave upon us causing profound impact on every sector of the economy and society. Reflecting on preceding technology waves, and using information systems principles as analytical lens, we describe their impact on business education and industry connectivity. Tighter industry-university relationships are absolutely necessary moving forward.

RETHINKING AI AND ITS IMPACT ON BUSINESS AND HUMANITY

Daniel Hulme

CEO, Satalia; CEO, Conscium; Chief AI Officer, WPP, UK

Description: Working in academia, the public and private sectors, Daniel is a globally recognised expert in Artificial Intelligence as well as its applications and the social, commercial, economic and ethical implications. In a world where many believe access to more and more data will lead to ever better decision-making, he looks at what AI really is, as well as identifying the current and future challenges and opportunities for emerging technologies. Daniel provides a radical new framework for thinking about AI, and discusses how organisations can practically adopt these technologies and avoid being seduced by the hype. He argues that whilst these technologies are incredible at creating growth and streamlining operations, for companies to stay innovative they need to also use AI to unlock the creative capacity of their workforce. Daniel also covers the macro impact these technologies may have on business and humanity over the coming decades.

RETHINKING AI AND ITS IMPACT ON BUSINESS AND HUMANITY

Jannis Kallinikos

Professor of Organization Studies, Luiss University, Rome, Italy; Professor Emeritus,
Department of Management, London School of Economics, UK

Description: Research on the organizational implications of AI is commonly framed in terms of the specific character of AI applications and the tasks such applications are brought to bear upon. Medical diagnoses, hiring or investment decisions, industrial engineering, language translation and content creation, autonomous driving, authentication through voice or face recognition represent typical examples. Important as it may be, such an understanding of AI ends up with a scattered list of possible AI interventions that fail to capture the core of ongoing changes and the distinct patterns by which AI reweaves the fabric of knowledge making and organizing. In my talk, I single out essential behavioural modalities through which social agents enact and shape organizational operations and map the likely effects of AI on perception (e.g. object recognition), interactive cognition (e.g. natural language processing and LLMs) and action (e.g. robotics). The objective is to outline the larger picture and spell out the key premises by which AI is involved in the exercise of expertise and the making of organizations.

AI: FROM RESEARCH TO IMPACT

Giorgio Metta¹ and Theodore Evgeniou²

¹CEO, Scientific Director Istituto Italiano di Tecnologia, ²INSEAD

Description: The talk will begin by highlighting emerging AI research themes with strong potential for future scientific and technological development, raising new questions and opportunities to address critical problems. We will then discuss how AI may create new possibilities to translate research into solutions, products and businesses, as well as the broader question of how labs and universities can improve the way research translates into impact. The discussion will also focus on what may need to be done in Europe to unlock the potential of research talent and ideas from the labs.

AI AND THE SKILLS REVOLUTION: PREPARING FOR WHAT'S NEXT

Byron Nicolaides
Founder & CEO, PeopleCert

Description: AI is fundamentally revolutionising the skills required to compete and lead. People and organisations that fail to adapt will inevitably become obsolete in the years ahead. According to the World Economic Forum, AI-driven automation is expected to displace 85 million jobs by 2025 and alter 40% of core skills required. In a world where knowledge evolves faster than traditional education models can adapt, how must educational institutions transform? What does the next-generation learner look like? What are the skills we must now acquire to remain employable, relevant, and competitive, and what are the jobs of the future? How should people and AI tools collaborate to unlock new levels of potential? For over 25 years, PeopleCert has been at the forefront of the skilling-reskilling-upskilling revolution. We are proud to be part of the dream-making economy with our motto being “Dream it, do it!”. To date we have empowered millions of learners, 50,000 companies (including 82% of Fortune 500), and 800 governmental organisations across 200+ countries to achieve what they are capable of.

ABSTRACTS

Session A1

**AI, GOVERNANCE AND
REGULATION**

**Chair: Eric K. Clemons, Wharton School, University of Pennsylvania,
USA**

ONE RING TO RULE THEM ALL? THE AI ACT THE EU'S QUEST FOR AI LEADERSHIP AND TECHNOLOGICAL SOVEREIGNTY

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Keywords: Artificial intelligence, governance, AI act, AI leadership, technological sovereignty.

Introduction

After several winters, Artificial Intelligence (AI) is now enjoying a blazing summer (Smuha, 2021), marked by substantial developments in machine learning, natural language processing (Supriyono et al., 2024) and generative AI applications (Stahl et al., 2023), record-level investments (Field and MacKenzie, 2024), and accelerating adoption (Aizenberg and van den Hoven, 2020; Rashid and Kausik, 2024). Yet, the rise of AI as a transformative and disruptive technology has intensified the global competition among major powers, including the United States (US), China, Russia, and the European Union (EU), for the leading position in AI development (Marino, Stilo and Serra, 2025). The close intersection of technology with politics and economics along with economic and technological dependencies, and the, recently growing, geopolitical tensions compel countries worldwide to assert control over their technological resources and infrastructures (Pohle and Thiel, 2020; Lambach and Oppermann, 2023), bringing technological sovereignty to the forefront of the global policy arena (Celeste, 2020; Floridi, 2020; Crespi et al., 2021; Roberts et al., 2021). Within this context, securing AI leadership has emerged as a strategic priority and a major point of international competition on multiple levels (Horowitz, 2018).

Whereas so far, the US and China have opted for market-driven and state-driven AI strategies, the EU has adopted a different approach, using policy to position itself as a leader in the pursuit of technological sovereignty (Celeste, 2020; Crespi et al., 2021; Lambach and Oppermann, 2023) and AI leadership (Siegmann and Anderljung, 2022; Christou, Meyer and Fanni, 2024). A rather profound manifestation of this perspective is the recently enacted EU Artificial Intelligence (AI Act), the world's first comprehensive legal framework on AI. The Act, which officially entered into force on August 1, 2024, adopting a risk-based approach (Schuett, 2023; Novelli et al., 2024), sets forth harmonised rules for the development, placement on the market, and usage of AI in the EU. Designed to balance innovation with public safety and human rights, the Act is expected to have significant implications beyond the EU borders, both due to its extraterritorial effect and thanks to the "Brussels Effect". Yet, more than setting a benchmark for other jurisdictions, the Act is critical to securing the EU's competitive advantage in the AI landscape and its technological independence.

This paper reviews the Act as a milestone in global AI governance and a strategic initiative in the quest for the EU's technological sovereignty and leadership in AI development (Hoffmeister, 2024). Employing a doctrinal legal analysis, it presents

the AI Act and examines its key provisions focusing on its merits and regulatory innovation (Section 2), thereafter placing it within the broader EU digital strategy it explores its role and potential in fostering innovation and competitiveness, reinforcing EU's leadership in AI, focusing and discussing the drawback of the Act and the impact they may have on the Act realizing its further objectives (Section 3). Finally, the article concludes with some remarks and recommendations. The article contributes to the growing literature on the EU AI Act, offering a less explored dimension (Christou, Meyer and Fanni, 2024), namely the role of the Act in the broader context of EU's quest for technological sovereignty and AI leadership.

The EU AI Act

The efforts of the EU to regulate AI and algorithms predate the AI Act. The foundations can be traced back to various policy documents, strategic frameworks, and ethical guidelines that have shaped the EU's approach to AI governance over the years. Central to the EU's approach towards AI governance is the commitment to fostering innovation premised on ethical principles, human-centric design and characteristics in line with fundamental rights and democratic principles (AI Commission, 2019; AI HLEG, 2019; European Commission, 2020). One of the earliest significant steps is the appointment of the high-level Expert Group on Artificial Intelligence (AI HLEG) (Cannarsa, 2021; High-Level Independent Group on Artificial Intelligence (AI HLEG), 2019b) in June 2018 by the Commission. AI HLEG was tasked to produce guidelines for the ethical use of artificial intelligence. Probably the most well-known Deliverable of the AI HLEG is the "Ethics Guidelines for Trustworthy AI", emphasising the key role of the EU Charter of Fundamental Rights for informing and guiding AI development, as well as introducing the EU definition of AI, along with the intensively discussed notion of "trustworthy AI" (AI HLEG, 2019). The recommendations instrumental in guiding the policymaking initiatives at the EU level, paving the way for the EU AI Act. Yet arguably the turning point that signified the shift from soft law instruments and ethics towards the development of a comprehensive binding framework was the White Paper on Artificial Intelligence published by the Commission in 2020. Emphasising the necessity for a coordinated EU strategy to harness the potential of AI while mitigating the risks, ensuring trust, transparency and accountability (European Commission, 2020), the White Paper set the stage for the AI Act.

On 9 December 2023, the European Parliament and the Council reached a provisional agreement on the final draft of the AI Act, after several changes and lengthy heated debates, across political, legal and technical aspects. It aims to establish a clear regulatory framework for the development and deployment of AI within the EU (Recitals 8 & 97), while addressing the ethical and fundamental rights concerns and the mitigating the risks and building trust on AI promoting human-centric and trustworthy AI (Article 1). The definition of AI is arguably a key aspect of the Regulation, crucial in defining the scope, shaping the legal obligations, and securing meaningful protection for fundamental rights. Hence, it is no surprise that it was a major point of debate and has been changed and amended several times (Almada and Petit, 2023; Kazim et al., 2023; Novelli et al., 2024). The adopted definition is relatively open, embracing a technology-neutral approach to encompass a wide range of existing and emerging technologies thereby preventing loopholes and, hopefully,

future-proofing the legislation. Turning to the scope and the jurisdictional reach of the Act, following the steps of the General Data Protection Regulation (GDPR), the AI Act also introduces extraterritorial effect as it applies to providers, deployers and users of AI systems within the EU, regardless of their geographical location, provided their AI systems have an impact on EU citizens (Article 2). As it will be further discussed in the next Section, this extraterritorial scope is critical in reinforcing the EU's leadership in setting global AI standard, and key to level the competition between EU companies and third countries' providers.

Among its key innovations is the risk-based classification and the specific provision for general-purpose AI. Aiming to balance innovation with fundamental rights and public interest classified and regulated based on their potential impact on fundamental rights and societal well-being.

Nonetheless, its broad phrasing raises concerns regarding regulatory clarity, legal certainty and potential overreach. Whereas there are several important definitions that are entirely new, the Act incorporates a lot of concepts that are already familiar from the product safety EU framework. The AI Act applies to providers, deployers, and users of AI systems within the EU, as well as entities outside the EU whose AI systems affect individuals within the Union. It covers a broad spectrum of AI applications, categorizing them based on their level of risk. The Act extends to public and private sector actors, including businesses, government agencies, and research institutions engaged in AI development and deployment. By adopting a horizontal approach, the regulation is designed to be applicable across industries, from healthcare and finance to transportation and education.

The AI Act represents a landmark regulatory effort that introduces a risk-based approach to AI governance, ensuring that AI applications are The Act prohibits AI systems deemed to pose an unacceptable risk, such as social scoring and real-time biometric surveillance in public spaces, while imposing strict compliance requirements on high-risk AI applications. These high-risk systems, which include AI tools used in healthcare, employment, law enforcement, and critical infrastructure, must adhere to transparency, accountability, and human oversight obligations. Additionally, the Act mandates explicit transparency requirements for limited-risk AI applications, such as chatbots and generative AI tools, ensuring that users are informed when interacting with AI-driven content. The Act also incorporates mechanisms such as regulatory sandboxes, which provide AI developers, particularly startups and SMEs, with controlled environments to test innovative AI solutions while complying with EU legal standards.

The impact of the AI Act extends beyond regulatory compliance, positioning the EU as a global leader in AI governance and technological sovereignty. By setting clear legal standards for AI development and deployment, the Act aims to enhance trust in AI technologies while fostering a competitive and ethically responsible AI ecosystem. Moreover, the Act strengthens the EU's strategic autonomy by reducing reliance on non-European AI technologies and ensuring that AI systems align with European fundamental rights. However, concerns persist regarding potential overregulation and its impact on innovation, particularly for smaller AI firms that may struggle with compliance costs. Additionally, the extraterritorial nature of the Act, similar to the GDPR, suggests that it may influence AI governance beyond

EU borders, shaping international AI regulatory norms and prompting global tech companies to align with EU standards to maintain market access.

References

Avison, D. E. and Fitzgerald, G. (1995). Information systems development: Methodologies, techniques and tools, 2nd Edition. London: McGraw-Hill.

Kude, T., Bick, S., Schmidt, C., and Heinzl, A. (2014). "Adaptation patterns in agile information systems development teams," in: Avital, M., Leimeister, J. M., & Schultze, U. (eds.) European Conference on Information Systems, Tel Aviv, Israel.

Markus, M. L. and Robey, D. (1988). "Information technology and organizational change. Causal structure in theory and research," *Management Science* 34 (5), 583-598.

A PRACTICAL GUIDE TO STRATEGY IN AN AGE OF INCOMPLETE REGULATORY SPECIFICATION AND POTENTIALLY UNLIMITED SOURCES OF LIABILITY

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Keywords: Risk-based regulation, risk-based compliance, regulatory ambiguity, regulation and EU competitiveness.

Risk-based regulation in the EU acknowledges that for rapidly evolving technologies it will not be possible for regulators to specify all failure modes, all abuses, and all risks associated with innovative implementations. It will be up to implementors to identify and manage risks themselves; that is, industries must regulate themselves, but remain liable for any harm they create. This is poorly understood, and has profound implications for European competitiveness. We explore why risk-based regulation of autonomous AI agents and technology platforms requires the rapid development of expertise to enable risk-based compliance, and why failure to do so threatens EU competitiveness in rapidly evolving technology-driven markets.

Risk-based compliance is new and it remains poorly understood (Gregorio and Dunn, 2022), but it has profound implications for corporations and for EU competitiveness. EU regulators are fully embracing it (Savin and Bagley, 2023), even though implementors, users, and the regulatory community itself, do not fully understand risk-based regulation or its implications (op. cit.). Risk-based regulation starts by shifting the decision of which risks to manage to the developers, implementors, and innovators (Baldwin 2015)—regulators no longer feel competent to identify all risks that innovations may create (Black and Baldwin, 2012).

Innovators must identify the risks associated with their products and services, identify those that create the greatest possible danger, and manage those risks down to acceptable levels. It is not clear how that can be done in instances when the usage modes of innovations are not known in advance and the unintended consequences of those usage modes cannot be identified. It is not clear what the innovators' liabilities will be when harm does occur. Is the mere fact that harm occurred, somewhere, and in some way connected with the deployment of the innovation, conclusive proof of the innovator's failure to comply with risk management? Is that fact sufficient to establish the innovator's legal liability?

Implementors remain liable for a wide range of problems that have not been explicitly described. Ultimately society will benefit from risk-based regulation, especially in the presence of technologies where regulators cannot anticipate all possible uses and cannot list all possible forms of harm. The entire concept of risk-based regulation may create a significant risk for the EU. Fear of litigation may reduce EU entrepreneur's willingness to undertake new developments when the risks cannot be identified. Remembering the sources of America's domination of the net, this may result in America's domination of future technologies.

Risk-based regulation requires that innovators make their best efforts to render a new product or service acceptably safe. In contrast, well-understood products have well-understood functionalities, well-understood usage modes, and well-understood

risk-mitigation built into their design. We have decades of experience with many consumer products, and can specify safety regulations for products ranging from hairdryers to automobiles. The developers of the first social media platforms did not anticipate the privacy risks from online platforms (Estrada-Jiménez, 2017), the possibility of online bullying (Vogels, 2021), the rise in teen alienation and loneliness (Gross, 2004), or the use of social media platforms to increase societal polarization (Ludwig and Müller, 2022), or for election manipulation (Aral and Eckles, 2019).

Risk-based compliance is not the same as risk-management in a traditional sense, because Traditional risk management assumes that you know what can happen, how likely it is to happen, and what harm it can cause (Clemons, 2019). Any time the probability of a failure mode is high, or the harm from a failure mode is high, the risk manager would reduce the probability of that specific failure mode or reduce the harm it caused. This assumes that it is possible to list failure modes and to estimate their probability and the harm associated with them. For new products, new services, or new platforms, this may simply be impossible. There are techniques that can be applied, such as scenario analysis, but they lack the precision required for true risk management. These techniques may not always be sufficient for planning and may not always be acceptable in litigation.

Similar problems are faced by pharmaceutical companies when they release a new treatment. Technology companies will need to gain comparable experience. Given the speed with which AI is being developed, extended, and deployed, technology companies and platform operators will need to gain comparable expertise in risk-based compliance and will need to do so rapidly.

The EU's new AI Act stresses that autonomous systems introduce their own forms of risk (AI Act, 2024), and that each autonomous system will have different usage modes, failure modes, and levels of harm from failure.

When autonomous decision-making affects life-and-death outcomes they require risk management. Autonomous systems that determine prison sentencing or the determine the level of bail have their own risks (Bagaric, 2019). The greatest risks are associated with systematic bias of any kind, including but not limited to, racial bias (Galaz, 2021). The AI Act demands that innovators and implementors identify these risks themselves, and then manage these risks to acceptable levels.

Disinformation in social media platforms refers to the intentional spreading of false information (Aïmeur, 2023). Lying can be good business. Inaccurate news stories can lead to users reading more material, posting more material, and being exposed to more paid advertising. Fake news stories are read more, are reposted and forwarded more, spread faster, and are more profitable for social media platforms (Bozarth and Budak, 2021). Social media platform executives have resisted attempts to limit disinformation campaigns (Pherson, 2021). Social media platforms' disinformation campaigns can be uniquely effective (Aïmeur 2023); stories can be written based on users' interests, and stories can be directed to the most vulnerable or the most sympathetic users, ensuring great impact.

Social media platforms have been used to motivate ethnic violence, as in Myanmar (Rio, 2021), or to enhance the power of autocratic rules, as in the Philippines (Arugay, 2022), or to motivate and celebrate terrorist acts, as in Christchurch (Leitch, 2022). To date the courts have not established a tight causal link between

any specific platform and any specific act of terrorism, and no social media platform has been held liable for the property loss, injury, or death from terrorism. Risk-based regulation and risk-based compliance suggest that platform operators will encounter legal liability in the future.

Numerous other examples exist, but space limitations prevent our listing them here.

We need a methodology for management of future exposure in the presence of strategic ambiguity, and this is seldom taught. Globally, future managers and executives in MBA programs are trained in quantitative management, the idea that their goal should be numerically specified, either to achieve the highest possible risk-adjusted rate of return, or to minimize downside risk, or other unambiguous objectives.

Innovators can be held liable when their products and services perform exactly as they were designed to perform, and have successfully passed all forms of software testing and user testing. Risk-based regulation shifts responsibility to the innovator, and an innovator can be held liable for harm caused by the innovation, even if the harm was not initially envisioned; risk-based regulation implies that the occurrence of harm can show that the innovator failed to manage risks properly. Risk-based compliance goes beyond traditional risk management, because the innovator usually lacks some of the information required for risk management. Experience suggests that simply because a problem was unforeseen does not always mean that it was unforeseeable.

References

Aïmeur, E. et al, “Fake news, disinformation and misinformation in social media: a review” (2023) 13 *Social Network Analysis and Mining* 30.

Aral S. and Eckles, D. “Protecting elections from social media manipulation” (2019) 365 *Science*, 858-861.

Arugay, A.A. and Baquisal, J.K.A. “Mobilized and polarized: social media and disinformation narratives in the 2022 Philippine elections” (2022) 95 *Pacific Affairs*, 549-573.

Bagaric, M. et al., “Introducing disruptive technology to criminal sanctions: Punishment by computer monitoring to enhance sentencing fairness and efficiency” (2019) *Brooklyn Law Review*, 84(4).

Baldwin, R. “Regulating Risks”, Ch. 6 in Baldwin, R. et al. *Understanding Regulation: Theory, Strategy, and Practice* (2nd edn, OUP 2015).

Black, J. and Baldwin, R. “When risk-based regulation aims low: A strategic framework” *Regulation & Governance* (2012) 6, 131–148.

Bozarth L. and Budak, C. “Market forces: Quantifying the role of top credible ad servers in the fake news ecosystem” In *Proceedings of the International AAAI Conference on Web and Social Media* (2021), Vol. 15, pp. 83-94.

Clemons, C, “Scenario Analysis and Managing Strategic Ambiguity: How to Remember Future Events, Before They Actually Occur!” Ch. 10 in E. Clemons, *New Patterns of Power and Profit* (Springer 2019).

Estrada-Jiménez, J. et al. J., 2017. “Online advertising: Analysis of privacy threats and protection approaches” (2017) *Computer Communications*, 32-51.

Galaz, V., et al. "Artificial intelligence, systemic risks, and sustainability" (2021) 67 *Technology in Society* 101741.

Gregorio, G. and Dunn, P. "The European Risk-Based Approaches: Connecting Constitutional Dots In The Digital Age" (2022) 59 *Common Market Law Review* 473–500

Gross, E.F. "Adolescent Internet use: What we expect, what teens report" (2004) 25 *Journal of applied developmental psychology*, 633-649.

Leitch, S. "The making of a 'made for social media' massacre" in Leitch, S. Pickerin, P. (eds.) *Social Media And Extremism* (Anu Press 2022), p.13. Ludwig, K. and Müller, P. "Does Social Media Use Promote Political Mass Polarization?" (pp. 118-166). Nomos Verlagsgesellschaft mbH & Co. KG. 2022.

Pherson, R.H. et al. "Strategies for combating the scourge of digital disinformation" (2021) 34 *International Journal of Intelligence and CounterIntelligence* 316-341.

Regulation (EU) 2024/1689 (Artificial Intelligence Act) OJ L, 2024/1689, 12.7.2024

Rio, V., "Myanmar: The role of social media in fomenting violence. In *Social media impacts on conflict and democracy*", pp. 143-160, (Routledge 2021).

Savin, A. and Bagley, C. "On A Strategic Management Approach to the New EU Risk-Based Compliance Regulations" (2023) 16 *International In-house Counsel Journal*, No. 63, Spring 2023.

Vogels, E.A. *The state of online harassment* (Vol. 13, p. 625). Washington, DC: Pew Research Center 2021.

TIME FOR THE EU TO MOVE FAST AND BREAK THINGS? LESSONS LEARNED FROM EXPERIENCE WITH RAPID INNOVATION

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Keywords: Regulatory ambiguity, innovation and entrepreneurship, AI competitiveness, EU.

Introduction and historical context

The strategic importance of AI has been rapidly increasing, in fields as diverse as entertainment, health care, finance and marketing, espionage, and national security. EU regulators know this, and one of the stated reasons for the AI Act was to position the EU as a major actor in AI. Experience with America's ability to innovate rapidly, in desktop software, internet infrastructure, search, and online social media, provides useful guidance for EU innovation.

The AI Act, as written, may have the reverse effect from what was intended, and may dramatically reduce the EU's ability to innovate in AI and its ability to remain competitive. The Act exacerbates the factors that have inhibited the EU's ability to innovate in a range of technologies, as diverse as desktop operating systems, office software, search, and social networks. Fortunately, there are concrete steps that can be taken by regulators, legislators, innovators, financial institutions, and universities, to facilitate EU innovation.

Although European industry remain competitive in many sectors, America and China clearly have provided the bulk of software innovation. European industries succeed in many sectors, including automotive design and production, optics, aerospace, power generation and transmission, and pharmaceuticals, where EU firms are all world leaders. SAP demonstrates that Europe can still produce world-class software. And yet, Europe has not produced the dominant player in any sector of the online world. From infrastructure like browsers and cloud computing, to apps like social media, the dominant players in the European marketplace are all American, like Microsoft, Alphabet, Meta, or now Chinese, like ByteDance (TikTok). But why? What is it that makes the online sector so different?

A key difference is that the online industry has network effects. Unlike pharma, automotive, or aerospace, where multiple global players can coexist, the online industry is a winner-takes-all market (Shapiro & Varian, 1999; Eisenmann et al., 2011). Google has been dominating search because it already has the most data. New search engines struggle to compete, even with superior technology. Facebook, WhatsApp, and Instagram benefit from social network effects, because people won't switch to a new platform unless all their friends do. In contrast, BMW, Honda, and Toyota all thrive because people don't all need to drive the same car.

In addition, again unlike other industries, the online early innovators can scale up faster and cheaper. In traditional industries like automotive, aerospace, and pharma, expansion requires huge upfront investment in factories, supply chains, and R&D. In the online sector, software scales at almost zero cost—once a platform is built, it can grow exponentially with minimal marginal cost.

Other important factors include the regulatory environment in effect, the existence of specialized clusters, the culture, and more.

In this paper we will draw from lessons learned, and present 4 initiatives that could help Europe move towards a position of leadership in AI. These are: a) clarifying the EU regulatory environment, b) developing a targeted strategy to develop specialized clusters, c) reforming the educational system, and d) taking initiatives to change the culture with respect to innovation and risk.

Clarifying the AI act

Published in July 2024, the EU AI Act is the main legislative framework for regulating AI in the EU. The Act entered into force in August 1, 2024 and will be effective from August 2, 2026. The EU has also proposed the AI Liability Directive designed to ensure that liability rules are appropriately applied to AI-related claims. This Directive was, however, withdrawn in February 2025 due to a lack of consensus among countries on core issues. Understanding the AI Act and how it may inhibit innovation in the EU is a prerequisite for regaining EU innovation and EU competitiveness in AI.

The EU AI Act applies extraterritorially and to all sectors. It intends to promote human-centric and trustworthy AI and to ensure a high level of protection of health, safety, fundamental rights, democracy, and rule of law from harmful effects of AI systems while supporting innovation and the functioning of the internal market. Key to the Act is the risk categorization of AI systems into 4 categories, depending on the level of risk they present: Unacceptable risk (prohibited), high risk (subject to detailed compliance), limited risk (required to disclose that the content has been artificially generated or manipulated), and low risk (the remainder).

Enforcement of the EU AI Act will involve a notifying authority and a market surveillance authority in each EU member state. The notifying authority will set up and carry out the assessment and designation procedures that are required under the EU AI Act. The market surveillance authority will be responsible for enforcement at the national level. If an AI system is non-compliant, the market surveillance authority can exercise enforcement. The market surveillance authorities will report to the Commission and to national competition authorities on an annual basis. An AI Office within the Commission will enforce the common rules across the EU. Enforcement will be supported by a scientific panel of independent experts. An AI Board with Member State representatives will advise and assist the Commission and Member States on the consistent and effective application of the AI Act. An advisory forum for stakeholders will provide technical expertise to the AI Board and the Commission.

The penalties of non-compliance are substantial.

In short, the AI Act is, first and foremost, about consumer protection, and not about innovation:

- Companies shall do no harm.
- Companies therefore shall not release any applications before they know that they are safe, and have acceptable risk, in all future situations, all future contexts, and all future usage modes.

In contrast, there is no comprehensive federal legislation or regulations in the US that regulate the development and use of AI. A large number of bills are being considered in the US Congress on things such as AI education, copyright disclosure, AI robocalls, biological risks, and AI & national security. There is an emphasis on the development of voluntary guidelines and best practices for AI systems, reflecting a cautious approach to regulation aimed at fostering innovation without imposing strict mandates. This approach is influenced by the race with China.

Exemplifying this, as soon as the current administration entered the White House it released the new Executive Order “Removing Barriers to American Leadership in AI” on January 23, 2025. The EO revoked the previous one from October 2023. The sole objective of the new EO was declared to be leadership in AI innovation.

The differences in approach between the two regions are, thus, stark. The EU AI Act is a pioneering move towards risk-based regulation and risk-based compliance. Some technologies are, however, evolving so quickly that regulators do not yet know what capabilities will be used, how they will be used, or how their users will interact with other systems or with other users. Rather than specify what can and cannot be done, or what must and must not be done, regulators require that implementors ensure that their systems will do no harm. Developers must identify for themselves how systems can produce harm, how great that harm will be, and how likely that harm is, and must manage the potential risk before bringing their products to the market.

It is thus possible that this pioneering regulatory approach of the AI Act towards risk-based regulation and risk-based compliance will, by its very design, inhibit innovation in the EU. With well-understood consumer products regulators can demand that, say, hairdryers remain safe from electrocution even when accidentally dropped into water, or that automobiles have skid protection and antilocking braking systems. In contrast, producers of autonomous systems must ensure that no harm occurs, even without the ability to specify for innovators what forms of harm they must avoid. Such regulatory ambiguity, combined with relative European risk aversion, can unintentionally lead to Europe continuing to be a follower instead of becoming a leader. What can be done here?

Regulators can attempt to provide mechanisms for documenting adequate steps to limit harm, which would be especially useful in future litigation when harm occurs. As written today, the AI Act seems to imply that any significant harm is sufficient demonstration of insufficient efforts at risk management. While some harm is unambiguously the result of malfeasance, misfeasance, and non-feasance, this is not always the case. While some future events cannot be anticipated, others should have been clear to innovators long before they occurred. Private discussions at a session chaired by Ariana Huffington at Davos debated the future of online information and disinformation. Ariana believed that Obama’s election victory signaled a return to the perfect Agora of Pericles; others feared that it would enable systematic misinformation and disinformation and the manipulation of the public in the manner of Alcibiades. Surely the developers of Facebook and Twitter cannot claim total surprise at the use of their platforms to manipulate voters and consumers.

At a minimum, regulators can demand adequate exploration of forms of harm. They can also provide a pathway where innovators can document that they per-

formed adequate planning and analysis, which should serve to mitigate innovators' liability for future harm. It is necessary that innovators can provide documentation of due diligence in case of future harm, knowing that due diligence cannot not always produce complete and perfect risk avoidance.

Creating/enhancing regional clusters and entrepreneurial ecosystems

A robust observation over the years has been that entrepreneurial activity is unevenly distributed in geographical space, a function of heterogeneous endowments in knowledge, institutions, resources, and demand. This generates a spiky geography of economic activities – accentuated by technological evolution (Adler et al., 2019; Florida and Mellander, 2016). This is important for our discussion here since simple observation has it that the most important private sector players in the dominant global power of AI tend to be located in a particular region of the country anchored around the San Jose – San Francisco S&T cluster and its extended tentacles in the western part of the country reaching north to Seattle and south to San Diego.

Europe has developed knowledge-intensive industry clusters over time. And yet, WIPO's Global Innovation Index 2024 indicates that the top European S&T cluster (Paris) ranks 12th internationally, the second European S&T cluster in line (London) ranks 21st followed by Munich on the 23rd and Amsterdam-Rotterdam on the 26th places. Stockholm ranks on 40th place (below Tehran in 38th). None of these European clusters are gaining positions, instead gradually dropping in the rankings despite active European policy. Notably, the San Jose-San Francisco cluster ranks 6th, the highest for the US and the Western world in general. All top five clusters are located in East Asia. This ranking is based on the location of inventors listed in published patent applications.

On the basis of a different metric – published scientific articles and patents divided by the population – Europe rises much stronger occupying three in the top six clusters (Cambridge, Eindhoven, Oxford), the remaining three being US-based (San Jose-San Francisco, Boston-Cambridge, San Diego). Several other European S&T clusters (12 in total) are in the top 25. The differences in the two rankings are revealing. European clusters are much stronger in science than in technology.

Entrepreneurial Ecosystems involve collaborative arrangements between firms and governments, institutions, universities, research institutes, sources of finance, incumbents, and entrepreneurial ventures (Stam & van de Ven, 2021). Accordingly, interactions and knowledge flows among agents and conditions compose the core of entrepreneurial ecosystems (Fischer et al., 2018; Fischer et al., forthcoming; Autio et al., 2018). Public programs recognize this by funding activities that incentivize spillovers, spur collective action, and leverage resulting synergies to achieve increasing returns to regional investment. These ecosystems are embedded in local contexts, contributing to intense heterogeneity in their constitutions, culture, capabilities, and economic orientation (Ács et al., 2017; Brown & Mason, 2017; Boschma & Martin, 2010). The interventions needed to enable the emergence of place-based innovation will vary with the conditions in each “place” (Cao & Shi, 2021; Ortega-Argilés, 2022).

None of the European clusters are leading powers in IT, less so in AI. Could they be? Can the EU help develop the collaborative arrangements between the players

mentioned above in a targeted way, that will spearhead the development and growth of leading AI entrepreneurial ecosystems?

Reforming the education system

As algorithms become more useful and more central to management, reliance on rigorous algorithms and large data sets have come to dominate business education, and our students are losing the ability to act rapidly in the presence of ambiguity and inadequate data. MBA programs often focus on teaching decision making, corporate strategy and related courses under a highly structured environment. They address complexity and can solve complex problems exactly using optimization and other computational capabilities. They differentiate between certainty, risk (where outcomes can be described by known probability distributions), or uncertainty (where the problem is risky, but the distribution parameters are not known). However, they rarely address situations where there is strategic ambiguity, i.e., situations where insufficient information exists, or where we do not know the probability distributions of the variables at play, or, even not what the variables are. In fact, the way we teach our courses increase ambiguity aversion and diminish ambiguity perception. And all of this, at times where strategic ambiguity is increasing. This implies that our MBA students are not optimally trained for today's fast changing environment. It also means that their mindset is geared towards a more stable environment, which implies an aversion towards risk taking.

It is possible for universities to do a better job teaching our graduates how to plan in the presence of ambiguity and insufficient data. We can teach them to perform due diligence better, which will be especially valuable in the presence of mechanisms for documenting due diligence. We can teach them to be comfortable with uncertainty, how to manage risks, embrace them as opportunities and tolerate failure. Lean startup methodology should be part of any business or engineering curriculum. Theoretical business plans should be replaced with real startup projects, where students launch, fail and iterate (Neck et al, 2014). It means encouraging faculty to commercialize their research, as opposed to only publishing papers. It also means creating more incubators at universities, launching initiatives like launchpad, creating student VC clubs, organizing student hackathons, and more.

Changing the culture

The nature of the online industry requires taking decisions in uncharted territories. The fast pace of change requires bold moves with insufficient data. And the entrepreneurial ecosystem in order to succeed, needs an environment where players (innovators, users, government, society) will feel comfortable with uncertainty and ambiguity, celebrate success, tolerate failure, and will be ready to invest in larger startups to help them scale up even more.

This requires an aggressive, "break the rules if necessary" approach. However, European firms lack this culture. According to Landier (2006) "In Europe, a serious social stigma is attached to bankruptcy. In the USA bankruptcy laws allow entrepreneurs who fail to start again relatively quickly and failure is considered to be part of the learning process. In Europe those who go bankrupt tend to be considered as "losers". They face great difficulty to nance a new venture." In contrast,

American firms embrace a philosophy of “move fast and break things,” of innovating, succeeding, and getting regulatory approval after the fact, after their success, and after their capture of a large and satisfied user base.

Hofstede’s cultural dimensions theory (Hofstede, 2001) provides a useful framework for understanding how national culture influences entrepreneurship. His research identifies six key cultural dimensions that have significant implications for entrepreneurial activity. These include individualism vs collectivism, the degree of uncertainty avoidance, long-term vs short-term orientation, power distance, masculinity vs femininity, and indulgence vs restraint. Using these dimensions, Hofstede gave specific examples of how culture shapes entrepreneurship for a number of countries. For the US, low uncertainty avoidance and high individualism have contributed to a “move fast and break things” culture, fostering high-risk, disruptive entrepreneurship. On the other hand, again according to Hofstede, Germany’s high uncertainty avoidance and long-term orientation have led to a preference for precision, planning and quality, focusing on incremental innovation rather than radical disruption.

What can be done towards changing the culture? It will not be easy, and it will take time. Also, changing this culture requires a multi-pronged approach that involves regulators, legislators, educators, incentives, and social norms. But it’s important that steps are taken.

One step could be to reform bankruptcy and labor laws to reduce fear of failure. Bankruptcy laws should not be punitive, making failure a career-ending event, but instead making it a learning experience. Rigid labor laws should be avoided, especially in the startups’ early stages, as they discourage rapid hiring and scaling because firing employees is costly and difficult. Another step would be to reform business and engineering education along the lines mentioned above. Other steps could be to increase high-risk investments through tax incentives (e.g., lower capital gains for startup investments), introduce more regulatory flexibility for startups (e.g., delay complex regulatory requirements until startups scale beyond a certain size), try to change public perceptions (by celebrating risk-takers and not just established companies), and more.

Conclusions

In this paper we presented four categories of initiatives that we believe could help Europe move towards a position of leadership in the AI space. It is very encouraging that European clusters are leading in science – as they say in finance, the fundamentals are there. However, Europe needs to move quickly to establish the entrepreneurial ecosystem that will help move the continent to a position of leadership in AI. European regulators, together with legislators, financial institutions, innovators and educators need to work together to enhance European capabilities and control over the European internet infrastructure.

References

- Ács, Z., Stam, E., Audretsch, D., & O’Connor, A. (2017). The lineages of the entrepreneurial ecosystem approach. *Small Business Economics*, 49(1), 1–10.
- Adler, P., Florida, R., King, K., & Mellander, C. (2019). The city and high-tech

startups: The spatial organization of Schumpeterian entrepreneurship. *Cities*, 87, 121–130.

Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, 12(1), 72–95.

Boschma, R., & Martin, R. (2010). The aims and scope of evolutionary economic geography. [Papers in Evolutionary Economic Geography #10.01]. Utrecht University - Urban & Regional Research Centre.

Brown, R., & Mason, C. (2017). Looking inside the spiky bits: A critical review and conceptualization. *Small Business Economics*, 49(1), 11–30.

Cao, Z., & Shi, X. (2021). A systematic literature review of entrepreneurial ecosystems in advanced and emerging economies. *Small Business Economics*, 57(1), 75–110.

Eisenmann, T., Parker, G., & Van Alstyne, M. (2011). Platform Envelopment. *Strategic Management Journal*, 32(12), 1270–1285.

Fischer, B. B., Vonortas, N. S., & Queiroz, S. (2018). On the Location of Knowledge-Intensive Entrepreneurship in Developing Countries: Lessons from São Paulo, Brazil. *Entrepreneurship & Regional Development*, 30(5-6): 612–638.

Fischer, B. B., Alves, A. C., Vonortas N. S., & Brown, R. (forthcoming). Foundations of Entrepreneurial Ecosystem Configurations. *The Journal of Technology Transfer*.

Florida, R. & Mellander, C. (2016). The Geography of Inequality: Difference and Determinants of Wage and Income Inequality Across US Metros. *Regional Studies*, 50: 79–92.

Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations* (2nd ed.). SAGE Publications.

Ortega-Argilés, R. (2022). The evolution of regional entrepreneurship policies: No one size fits all. *Annals of Regional Science*, 69: 585–610.

Shapiro, C., & Varian, H. R. (1999). *Information Rules: A Strategic Guide to the Network Economy*. Harvard Business School Press.

Stam, E., & van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics*, 56(2), 809–832.

White & Case “AI Watch: Global Regulatory Tracker” (<https://www.whitecase.com/insight-our-thinking/ai-watch-global-regulatory-tracker#home>). Accessed March 3, 2025. World Intellectual Property Organization (2024) *Global Innovation Index 2024: Unlocking the Promise of Social Entrepreneurship*, Geneva.

ALIGNING STAKEHOLDER VALUES IN DATA GOVERNANCE: A VALUE-SENSITIVE ANALYSIS OF THE EU DATA ACT

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Keywords: EU data act, value sensitive design, regional policy, data governance, NLP, LLMs.

Introduction

The EU Data Act represents a transformative legislative framework designed to balance competing priorities in Europe’s data economy: fostering innovation through data accessibility while safeguarding citizen rights (European Commission, 2022c). This study addresses the central research question: How do the values of diverse stakeholders influence the design of the EU Data Act? By analyzing 102 stakeholder letters submitted during the EU Data Act consultation process, this research employs Value-Sensitive Design (VSD) as a theoretical lens and uses machine learning methodologies to systematically compare stakeholder priorities with the finalized legislation.

The EU’s data governance framework operates within a complex ecosystem of competing interests. On one hand, businesses emphasize maximizing data utility for innovation and market competitiveness (Cecez-Kecmanovic, 2019), while civil society groups advocate for ethical safeguards against surveillance capitalism (Zuboff, 2015). This tension reflects broader debates in information systems (IS) research about balancing economic imperatives with ethical responsibilities in data-driven environments.

The findings reveal divergent value priorities between stakeholders and EU policymakers, highlighting tensions between sector-specific economic interests and broader ethical imperatives. While stakeholders prioritized Universal Usability and Ownership and Property to facilitate data-driven innovation, the EU Data Act emphasized Accountability and Freedom from Bias, underscoring its commitment to algorithmic fairness and regulatory compliance (European Commission, 2021b). This misalignment raises critical questions about whose values shape regional data governance frameworks and how policymakers reconcile conflicting priorities.

Theoretical background

Value-Sensitive Design (VSD) provides a robust framework for analyzing how stakeholder values shape technological and policy ecosystems, making it particularly apt for studying the EU Data Act’s development. Originating in human-computer interaction (Friedman & Kahn, 2008), VSD systematically integrates ethical considerations into design processes by emphasizing three investigative phases: conceptual (theoretical grounding of values), empirical (human responses to technology), and technical (system evaluations). In policy contexts like the EU Data Act, VSD enables policymakers to identify, prioritize, and reconcile competing stakeholder values while addressing ethical imperatives (Friedman et al., 2019).

The EU Data Act operates within a tension between economic imperatives (e.g., data accessibility for innovation) and ethical safeguards (e.g., privacy, algorithmic fairness). Businesses often prioritize values like Universal Usability and Ownership and Property to maximize data utility, while civil society advocates for Privacy and Freedom from Bias to mitigate risks like surveillance capitalism (Zuboff, 2015). VSD's participatory approach bridges these divides by engaging stakeholders in value identification, ensuring policies reflect diverse socio-cultural priorities (Friedman et al., 2013). For instance, the GDPR's enforcement against opaque data practices—such as the €50 million fine against Google for inadequate transparency (European Data Protection Board, 2019)—illustrates the clash between corporate interests and regulatory ethics. VSD provides a structured methodology to navigate such conflicts, as seen in its application to AI governance (Polyviou & Zamani, 2023) and data-sharing frameworks.

The EU Data Act exemplifies VSD's relevance to regional governance. By codifying values like Accountability and Informed Consent, the Act reflects the EU's commitment to balancing stakeholder input with ethical guardrails. VSD's conceptual phase aligns with the EU's emphasis on "digital constitutionalism", where policies protect fundamental rights in data ecosystems.

This framework also addresses the challenge of sector-specific vs. universal standards. While stakeholders advocate tailored governance (e.g., automotive data-sharing frameworks), the EU adopts horizontal regulations to prevent fragmentation. By grounding the EU Data Act's design in VSD, this study illuminates how regional governance frameworks can balance stakeholder diversity with cohesive policy outcomes, fostering innovation while upholding ethical imperatives.

Methodology

We analyzed 102 stakeholder recommendation letters (1,035 paragraphs, 279,165 words) submitted during the EU Data Act's 2021 consultation and the final legislative text. A custom VSD Value Classifier was developed using GPT-3.5 and RoBERTa to categorize text into the 12 VSD values (e.g., Privacy, Accountability). The classifier was fine-tuned with EUBERT, a BERT variant pre-trained on EU policy documents (Campion, 2023), achieving 98.1% accuracy in validation tests.

Quantitative alignment between stakeholder recommendations and the EU Data Act was measured using Earth Mover's Distance (EMD) and Cosine Similarity scores. EMD quantified the effort required to transform stakeholder value distributions into the EU's distribution, while Cosine Similarity assessed directional alignment. Stakeholder influence was weighted by submission volume and alignment scores. Qualitative analysis employed Latent Dirichlet Allocation (LDA) topic modeling (Blei et al., 2003) to identify latent themes within the top five stakeholder and EU values.

Results

Divergent Value Priorities: Stakeholders prioritized Universal Usability, emphasizing sector-specific data-sharing protocols (e.g., automotive industry standards), and Ownership and Property, focusing on intellectual property rights. In contrast, the EU Data Act emphasized Freedom from Bias, with clauses targeting algorithmic

discrimination mitigation, and Informed Consent, mandating transparency in data usage. For example, majority of the EU’s text on algorithmic systems included requirements for impact assessments, whereas only traces of stakeholder submissions addressed this issue.

Stakeholder Influence: Business associations, representing 45 submissions, exhibited the strongest alignment with the EU Data Act (Normalized Influence Score: 0.185). Their recommendations, such as standardized interoperability protocols, were frequently codified into the legislation. Conversely, consumer organizations (2 submissions) and academic institutions (5 submissions) had negligible impact, reflecting power imbalances akin to those observed in GDPR implementation.

Latent Themes Identified: LDA revealed divergent interpretations of shared values. Under Accountability, stakeholders framed compliance as cost management (e.g., “streamlining GDPR adherence”), while the EU emphasized punitive measures (e.g., “penalties proportional to infringement severity”). Similarly, stakeholders viewed Environmental Sustainability through regional innovation (e.g., “data hubs for agricultural efficiency”), whereas the EU linked it to systemic resource management (e.g., “data-driven climate mitigation”).

Discussion & contributions

The EU Data Act reflects a deliberate prioritization of ethical imperatives over sector-specific stakeholder demands. Three key tensions emerge:

Ethics vs. Economics: Stakeholders emphasized data monetization strategies, with automotive groups advocating proprietary control over vehicle-generated data. The EU emphasizes “user right to data access,” prioritizing consumer rights over corporate interests. This mirrors the GDPR’s enforcement against Google’s opaque data practices (European Data Protection Board, 2019).

Sector-Specific vs. Universal Standards: Industry requests for vertical governance frameworks conflicted with the EU’s horizontal approach. For example, while telecom firms sought exemptions for network data, the Act mandates standardized APIs for all IoT devices.

Algorithmic Accountability: The EU’s emphasis on Freedom from Bias addresses risks highlighted by the COMPAS recidivism algorithm scandal (Angwin et al., 2016). Mandatory impact assessments exceed stakeholder recommendations but align with academic calls for algorithmic transparency (Diakopoulos, 2016).

This study contributes to the discussion on regional data governance by systematically analyzing how stakeholder values shape legislative frameworks, advancing both theoretical and methodological frontiers. Theoretically, it extends the application of VSD to policy contexts, demonstrating its utility in reconciling ethical imperatives with economic priorities (Friedman et al., 2019). Methodologically, the development of a machine learning-driven VSD classifier—fine-tuned on EU legal texts—represents a novel approach for analyzing large-scale policy documents and stakeholder inputs, bridging gaps between NLP techniques and legislative analysis. Empirically, the study uncovers divergent priorities: stakeholders emphasized Universal Usability and Ownership and Property to drive sectoral innovation, while the EU prioritized Accountability and Freedom from Bias to uphold ethical safeguards (European Commission, 2022c). By quantifying stakeholder influence through met-

rics like Earth Mover's Distance, the study reveals the disproportionate impact of Business Associations compared to NGOs and academia, challenging assumptions about democratic policymaking in digital governance (Cecez-Kecmanovic, 2019). Practically, these insights offer policymakers a framework to balance stakeholder engagement with ethical imperatives, while providing businesses with strategies to align operations with emerging regulatory expectations.

References

Angwin, J., Larson, J., Mattu, S. and Kirchner, L., 2016. Machine bias: There's software used across the country to predict future criminals. And it's biased against blacks. *ProPublica*, 23, pp.77–91.

Cecez-Kecmanovic, D., 2019. The resistible rise of the digital surveillance economy: A call for action. *Journal of Information Technology*, 34(1), pp.81–83.

European Commission, 2021b. Proposal for a regulation of the European parliament and of the council on European data governance (Data Governance Act). Retrieved 1 November 2023, from <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52020PC0767>.

European Commission, 2022c. Regulation of the European parliament and of the council on harmonised rules on fair access to and use of data (Data Act). Retrieved 10 November 2023, from <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2022%3A68%3AFIN>.

European Commission, 2024. Shaping Europe's digital future - Data Act. Retrieved 19 January 2024, from <https://digital-strategy.ec.europa.eu/en/policies/data-act>.

European Data Protection Board, 2019. The CNIL's restricted committee imposes a financial penalty of 50 Million euros against GOOGLE LLC. Retrieved 24 January 2024, from <https://edpb.europa.eu/news/national-news/2019/cnils-restricted-committee-imposes-financial-penalty-50-million-euros.en>.

Friedman, B., Hendry, D.G. and Borning, A., 2019. Value sensitive design: Shaping technology with moral imagination. Cambridge, MA: MIT Press.

Friedman, B., Kahn, P.H. and Hagman, J., 2008. Value sensitive design and information systems. In K.E. Himma and H.T. Tavani, eds. *The handbook of information and computer ethics*. Hoboken, NJ: Wiley, pp.69–101.

Polyviou, A. and Zamani, E.D., 2023. Are we nearly there yet? A desires & realities framework for Europe's AI strategy. *Information Systems Frontiers*, 25(1), pp.143–159.

Zuboff, S., 2015. Big other: Surveillance capitalism and the prospects of an information civilization. *Journal of Information Technology*, 30(1), pp.75–89.

LEVERAGING AI IN THE PARLIAMENTARY GOVERNANCE SYSTEM OF THE HELLENIC REPUBLIC

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Keywords: Artificial intelligence, governance, AI strategy, AI governance, capacity building, regulatory impact assessment, Greece.

Introduction

The rapid evolution of AI technologies is reshaping global governance, economies, and societies. From the United States' (US) ambitious \$500 billion Stargate project to China's DeepSeek advancements, the global AI race is accelerating, prompting nations to rethink their strategies and investments in this transformative technology. The European Union (EU) has also stepped up its response, with initiatives such as the recent announcement of a €200 billion mobilization to bolster AI and digital infrastructure. However, the EU's approach to AI remains uncertain, as does its ability to compete with the technological dominance of the US and China. This debate is particularly relevant as some EU countries, including Greece, are poised to take a significant step forward with the development of AI Factories.

Within this context, this paper aims to outline an approach and framework for the effective integration of AI in governance, ultimately guiding the development of a comprehensive AI strategy. We outline two key types of AI-related investments: those focused on building AI capabilities, including complementary technologies and assets, and those centered on specific AI applications. The proposed AI applications portfolio is structured across themes relevant to the specific context. This approach can also help identify quick wins, that is "low-hanging fruits" that can deliver immediate impact, alongside longer-term strategic investments that lay the foundation for sustained AI integration. The objective is to contribute to an urgently needed AI adoption and maturity discourse in order to support nations, with particular focus on Greece, to remain competitive in an increasingly AI-driven global landscape.

Investing in AI Capabilities

Successful integration of AI into a governance system requires addressing various capabilities building needs to support AI applications across different functions. First, establishing an AI governance framework is central to supporting an AI strategy, ensuring alignment across institutional, national, and potentially European levels. Such an AI governance framework must, for example, ensure coherence between the National AI Strategy, the PACE framework convention, and the EU AI Act, creating a unified vision that balances innovation with appropriate safeguards while ensuring successful coordination of multiple and diverse stakeholders.

Second, infrastructure and cybersecurity frameworks specifically designed for AI systems need to be developed. These need to address the unique characteristics, needs, and vulnerabilities of AI systems, such as adversarial attacks and data or model poisoning, while establishing clear protocols for AI incidents monitoring, response, and recovery. The establishment of the National Cybersecurity Authority (NCA) in Greece represents a significant advancement in the nation's cybersecurity

landscape. Also, in view of the development and operationalization of the AI Factories, infrastructure readiness forms a vital prerequisite, requiring not only computational resources but also AI security as well as safety and data management systems capable of handling the volume, variety, latency, and quality of information needed for effective AI applications within the context of critical governance applications.

Third, skills supported with comprehensive training programs represent another critical horizontal factor, requiring targeted educational initiatives for technical personnel, policymakers, and end-users across governance entities. These programs must cover, among other aspects, the skills needed for defining, prioritizing, developing, deploying, adopting, and monitoring AI solutions. They should also address ethical and human factors in algorithmic decision-making and ensure proficiency in using relevant AI tools within governance contexts. Capacity building efforts must extend beyond technical training to also promote, for example, cultural readiness, innovation and value-focused mindsets, and institutional acceptance. On the same note, leadership engagement represents a critical success factor, requiring executive-level champions who understand both the transformative potential and implementation challenges of AI in governance settings. Leaders in governance must be able to articulate compelling, clear, and operational visions, secure necessary resources and manage political complexities while maintaining focus on long-term strategic objectives. Middle management, particularly heads of units and departments, might require specialized support as they will ultimately translate AI strategies into operational realities, balancing innovation imperatives with organizational constraints and managing any resistance to technological change.

Fourth, personnel across all levels of governance organizations need appropriate support structures to adapt to AI-enhanced workflows, including clear communications about how AI will impact roles as well as create new opportunities and challenges, support for skills development, change management, mechanisms to provide feedback on implementation challenges, and others. Throughout this process, the governance ecosystem should balance the efficient use of existing relevant work with the ability to develop new frameworks, processes, roles, organizational structures, and practices when needed, while building as needed upon established frameworks from international organizations and pioneering solutions in the parliamentary workspace.

Developing an AI Applications Portfolio in the Parliamentary Context

An AI strategy is in essence the development of a portfolio of AI investments, and much like any portfolio, these investments are of different types and need to be organized, rationalized, prioritized, and managed effectively. We show how a seemingly diverse list of technological possibilities can be structured into a framework—in this case, as a starting point, consisting of four parts: the first two related largely to process efficiency investments, and the latter two on engagement improvements related ones—that can guide the development of a parliamentary AI strategy. For this, groupings of AI applications that are currently being considered in the Hellenic public administration were identified, which reflect the complex needs of contemporary institutions.

In the current context, we focus on AI applications at the intersection of government and parliament, as well as their implementation within the parliamentary

workspace. While not exhaustive by any means, our objective is to provide a starting AI portfolio framework for identifying AI opportunities in parliamentary governance. For this, we outline specific AI applications within each of the discussed parts of the framework.

Legislative Support and Compliance

At the legislative level, AI tools can fundamentally transform how laws are developed, analyzed, and integrated into the broader legal framework. Based on empirical research, the focus could be on developing advanced systems that can analyze draft laws and highlight critical interactions with existing legislative provisions. A further transformative approach involves translating legislation into machine-readable code (e-code), which could dramatically accelerate the integration of regulations into digital processes. This includes sophisticated capabilities such as automatic classification of laws into thematic categories, identifying legislative provisions based on specific criteria and comprehensive amendment analysis. Moreover, by utilizing AI, the parliament can create more precise, interconnected, and accessible legislative documentation. More elaborate legislative support may be provided via AI-based regulatory impact assessment and evaluation tools. Finally, AI can be leveraged to help share lessons and knowledge across countries, for example to draft laws vs. EU directives in the case of the EU.

Ex-ante support could involve the drafting of Regulatory Impact Assessment (RIA) reports. Such tools can systematically analyze proposed legislation by processing vast amounts of historical data, social and economic indicators, and stakeholder feedback, providing predictive insights into potential legislative impacts, thus pointing at unintended consequences. Complementing this, ex-post tools, e.g., for conducting post-legislative scrutiny, could enable the evaluation of implemented laws by aggregating data from multiple sources to track effectiveness, compare outcomes against original objectives and generate detailed reports that support evidence-based policy refinement.

MP Support

We acknowledge the crucial role of MPs both as users of AI-driven tools and as legislators actively shaping AI governance frameworks, and aim to provide them with value-creating AI support. Intelligent systems can be developed to assist MPs in their legislative work and enhance their communication with constituents. This includes advanced data analysis and visualization tools and digital assistants that can transform complex information into comprehensible insights. These digital assistants would be designed to integrate seamlessly with MPs' workflows, offering for example intelligent document retrieval and broader knowledge management support, contextual research support, and communication refinement. These AI tools can significantly improve the efficiency and effectiveness of the MPs' work if developed and adopted successfully.

Citizen Engagement and Communication

Public consultation represents a critical avenue for democratic participation and AI can significantly enhance these processes. For example, Greece's opengov.gr platform can be revolutionized through advanced AI tools that analyze public comments during bill consultations. These tools could detect or even filter out hate speech in real time, mitigate groupthink and polarization, and flag unproductive,

biased or toxic discourse. They could also generate detailed Public Consultation Reports, offering deep insights into stakeholder proposals, including impact analyses and precise acceptance/rejection rates for each proposal in the final text. AI can support and potentially enhance transparency and citizens' participation in democratic processes. Digital assistants could be developed to provide clear, accessible explanations of complex special legislation. These intelligent systems would help citizens understand their rights and obligations across various domains, such as pension entitlements, regulations for short-term rentals, and guidelines for starting small businesses. Ultimately, by simplifying complex legal language, these AI tools can make government actions and information more transparent and accessible to the public.

Institutional Innovation and Communication

The overarching vision is to develop AI solutions that improve operations at both institutional and administrative levels. This involves creating intelligent systems for information and document retrieval, integrating natural language processing into the parliamentary website, and developing digital platforms that serve citizens and stakeholders alike more accurately, effectively, and efficiently. Beyond technological implementations, emphasis should also be placed on communicating AI-related initiatives. This could include expanding current practices, such as hosting panel discussions on parliamentary television channels to explore AI innovations, while also utilizing institutional publications to enhance transparency and public understanding of these technological advancements.

The long list of AI applications in parliamentary work and their diverse uses demonstrates AI's potential to boost operational efficiency and effectiveness, support democratic engagement, and advance the institution's mission through technological leadership. The deployment of AI systems represents a major step toward greater institutional efficiency and transparency, with the EU AI Factories well positioned to also possibly support these efforts. A solid AI strategy can greatly support the parliaments for their important role and mission.

Discussion and Next Steps

While this work focuses on establishing a foundation for developing an AI strategy in a parliamentary governance system, the primary challenge lies in implementing this strategy effectively. To begin with, this requires an appropriate prioritization of investments and projects to ensure a successful AI maturity journey. This prioritization should account for multiple factors, including: existing capabilities, organizational resistance, senior sponsorship and support, technical limitations, regulatory constraints, and overall feasibility. It must also consider interdependencies among AI initiatives and each investment's potential value, recognizing that some benefits may be measurable while others are harder to quantify. Crucially, both the development and execution of a parliament's AI strategy must align with the existing governance framework of the Executive State, the organizational and operational structure of the executive branch of government. Ultimately, for a national governance AI ecosystem to work successfully, teamwork—among the government, the parliament, the judiciary system, academia, the private sector, and perhaps also the EU AI Factories and other EU and national AI initiatives—is necessary for success.

AI presents significant opportunities to modernize governance institutions by

enhancing their efficiency, transparency, and accountability. This paper provides a starting point for developing an AI strategy in the context of the parliamentary governance system, with an emphasis on the Hellenic Republic, with particular attention to its application at the executive-legislative interface. The proposed approach balances alignment with national priorities and European initiatives while accounting for the distinct characteristics of parliamentary and national governance systems. The horizontal AI capability-building investments as well as the four types of AI applications discussed, i.e., legislative support, citizen engagement, MP support, and institutional innovation, illustrate the transformative potential of AI for the governance ecosystem.

Session B1

**FINANCIAL MANAGEMENT IN THE
AI ERA**

Chair: Stefano Bonini, Stevens Institute of Technology, USA

“PLATFORMIFICATION” OF BANKING: STRATEGY AND CHALLENGES OF CHALLENGER VERSUS INCUMBENT BANKS IN RESPONSE TO REGULATORY CHANGE IN THE UK

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Keywords: Platform formation, competition, regulatory change, incumbent strategies, industry architecture.

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Long Abstract

The financial technology (fintech) ‘revolution’ that started nearly 15 years ago in conjunction with more recent regulations around data portability in banking have led to an increase in the number of startups entering the banking industry with innovative business models (Murinde et al., 2022). A key business model that new financial technology companies (fintechs) and digital banks have been experimenting with is the platform business model. Platforms use technology to connect people, organizations, and resources in an interactive ecosystem where value can be created and exchanged (Parker et al., 2016). They facilitate interactions and matchmaking between consumers and producers, creating a multi-sided market that co-creates value (Rochet & Tirole, 2006; Zhu & Iansiti, 2012). Platforms typically reduce transaction costs by improving search, contracting, negotiation, and user experience (Munger, 2015; Benzel et al., 2017), and foster innovation through knowledge integration (Baldwin & Clark, 2000; Baldwin & Woodard, 2009; Gawer, 2009, 2014). Data plays a crucial role by reducing transaction costs and enabling personalization (Hagiu & Wright, 2023; Van Alstyne et al., 2016).

Due to these advantages, platforms have become central to many industries and markets such as e-commerce (e.g. Amazon, eBay), social media (e.g., Facebook, Twitter), video games (e.g. Xbox, Playstation), PC/mobile operating systems (e.g. Google Android, Apple iOS), and peer-to-peer sharing (e.g., Uber, AirBnB). While platforms have also attracted the attention of management, economics and other scholars, much of the research done concerns platforms that were developed by digital-born companies; and thus, questions remain regarding how traditional firms in established industries can switch to a platform business.

One of the most central questions when considering platforms as a form of organizing economic activity at the firm level is what boundary choices and governance decisions make a platform successful (Boudreau, 2017; Gawer, 2021a). A platform’s curation (i.e., how open a platform is to external contributors) and who makes these decisions can significantly influence its evolutionary trajectory (Gawer, 2014).

These issues become more problematic when considering that platform ecosystems are inherently dynamic and context-dependent. For example, in an unregulated, nascent market, platform competition might occur differently compared to a highly-regulated, mature industry – such as financial services – where existing players feel the pressure to transition from pipeline to platform business models to compete with new entrants. Platform creation by new ventures in a highly regulated industry might be difficult due to high entry barriers and high operational costs (Ozalp et al., 2022; Parker et al., 2016). Furthermore, sensitivity of data and associated privacy concerns in highly regulated environments (Ozalp et al., 2022; Markovich and Yehezkel, 2024) can create additional challenges both for new entrants as well as existing players that might want to transition to a platform business model. Many of these context-dependent aspects of platform competition have received little attention from management scholars (Altman and Tushman, 2017; Gawer, 2014; Schilling, 2000; Tiwana et al., 2010). Uncovering these dynamics is crucial in improving our understanding of how regulated industries evolve and become more innovative.

To help fill this gap, our study investigates *the advantages and challenges new players versus incumbents face in forming a platform business model in a highly regulated industry*. Through semi-structured field interviews, observations and archival research in the UK retail banking sector, we observed the emergence of financial platforms and the challenges established as well as new players faced around platform ownership and curation.

Contrasting the advantages and challenges of incumbents and new entrants in platform ownership and curation, we find that new entrants, a.k.a. challenger banks in our setting, faced little or no challenges in building their own platform due to their technical capabilities, skilled developers, and digital-born culture. They also chose to curate their platforms so that they were open towards complementors, i.e. fintechs, due to not having many financial products to start with. On the other hand, these players faced severe challenges in growing their platforms on the user side in a data sensitive industry, where customers were particularly weary of fully switching to new and largely unknown players.

In contrast, banking incumbents had a large user base, giving them an advantage in jumpstarting network effects. However, they faced challenges due to their fragmented IT infrastructures, a siloed and compliance-focused organizational culture, and limitations to data analysis. These issues hindered their ability to build and grow their own platforms, especially from the side of the complementors. This was evident in our sample which demonstrated the lack of successful incumbent platforms after several years of observations, and in spite of challenger bank platforms coming into existence during the same time. Incumbents also struggled with platform curation due to regulatory challenges as well as concerns around branding and competition. In a move to mitigate those challenges, the industry witnessed the emergence of third-party platforms that sought to assist incumbents in growing their platform propositions by offering ready-made solutions. This, however, created conflicts of interest and often resulted in the creation of ‘closed’, suboptimal platforms for bank users.

Our theoretical model that emerges from the findings provides a mental map for the two critical choices and trade-offs faced by organizations in the process of

platform formation: whether or not to build the platform themselves (platform ownership), and how open to keep it (platform curation). Through this mental map, we contribute to the ongoing discussion around “openness-versus-control” in the platform literature (Boudreau, 2017; Shapiro & Varian, 1998; West, 2003), but also taking into account the dynamic and ever evolving nature of platforms and their immediate context (Gawer, 2014; Tiwana et al., 2010). Our findings are highly generalizable to other regulated industries where the platform business model threatens to disrupt existing pipeline models. In particular, we emphasize that incumbents and new players in regulated industries with data sensitivity (e.g. healthcare, insurance) are particularly prone to the challenges and trade-offs that we describe in this paper. In the rest of the document, we first provide an overview of the theoretical underpinnings of platform research, then describe our research methodology and findings, and conclude with our contributions to extant literature on platforms and industry disruption.

References

- Altman EJ, Tushman ML. 2017. Platforms, Open/User Innovation, and Ecosystems: A Strategic Leadership Perspective: 177–207. Available at: <http://www.emeraldinsight.com/doi/10.1108/S0742-332220170000037007>.
- Baldwin CY, Clark KB. 2000. *Design Rules: The Power of Modularity* (Vol. 1, MIT Press: Cambridge, MA).
- Baldwin CY, Woodard CJ. 2009. The architecture of platforms: A unified view. In *Platforms, Markets and Innovation*, Gawer A (ed). Edward Elgar Cheltenham: 19–44.
- Benzell SG, Lagarda G, Van Alstyne M. 2017. The Impact of APIs on Firm Performance. Working Paper February.
- Boudreau, KJ 2017 Platform-Based Organization and Boundary Choices: Entrepreneurship, Innovation and Growth in the Early History of Mobile Computing. *Advances in Strategic Management on “Entrepreneurship, Innovation, and Platforms.”* eds. Furman, Gawer, Stern, Silverman.
- Christensen, C. M. and Bower, J. L. 1996. Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal*, 17: 197–218.
- Christensen, C. M., Raynor, M., & McDonald, R. (2015). 17. Disruptive innovation. *Harvard business review*, 93(12), 44–53.
- Gawer A. 2009. Platform dynamics and strategies: from products to services. *Platforms, markets and innovation*. 45:57.
- Gawer A. 2014. Bridging differing perspectives on technological platforms: toward an integrative framework. *Research Policy* 43: 1239–1249.
- Gawer, A. 2021a. Digital platforms and ecosystems: remarks on the dominant organizational forms of the digital age. *Innovation*, 1–15.
- Hagi, A., & Wright, J. (2020). Platforms and the exploration of new products. *Management Science*, 66(4), 1527–1543.
- Markovich, S., & Yehezkel, Y. (2024). “For the public benefit”: Data policy in platform markets. *Journal of Economics & Management Strategy*.
- Munger M. 2015. Coase and the ‘Sharing Economy,’ (chapter 9, pp. 187–208). In *Forever Contemporary: The Economics of Ronald Coase*. Edited by Cento Vel-

janovski. London: Institute for Economic Affairs.

Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022). The impact of the Fin-Tech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis*, 81(102103). <https://doi.org/10.1016/j.irfa.2022.102103>

Ozalp, H., Ozcan, P., Dinckol, D., Zachariadis, M., & Gawer, A. 2022. “Digital colonization” of highly regulated industries: an analysis of big tech platforms’ entry into health care and education. *California Management Review*, 64(4), 78-107.

Parker GG, Van Alstyne MW, Choudary SP. 2016. *Platform Revolution: How Networked Markets Are Transforming the Economy and How to Make Them Work for You*. WW Norton & Company.

Rochet JC, Tirole J. 2006. Two-sided markets: a progress report. *The RAND Journal of Economics* 37(3): 645-667.

Schilling MA. 2000. Toward a general modular systems theory and its application to interfirm product modularity. *Academy of Management Review* 25(2): 312-334.

Schueffel, P. (2016). Taming the beast: A scientific definition of fintech. *Journal of Innovation Management*, 4(4), 32-54.

Shapiro, C., & Varian, H. R. (1998). Versioning: the smart way to. *Harvard business review*, 107(6), 107.

Tiwana A, Konsynski B, Bush AA. (2010). Research commentary—Platform evolution: Coevolution of platform architecture, governance, and environmental dynamics. *Information Systems Research* 21(4): 675-687.

Van Alstyne MW, Parker GG, Choudary SP. 2016. Pipelines, platforms, and the new rules of strategy. *Harvard Business Review* 94(4): 54-62.

West J. 2003. How open is open enough?: Melding proprietary and open source platform strategies. *Research policy* 32(7): 1259-1285.

Zhu F, Iansiti M. 2012. Entry into platform-based markets. *Strategic Management Journal* 33: 88–106.

SEMI-SUPERVISED GRAPH-INFORMED FRAUD DETECTION IN PUBLIC REVENUE: THE CASE OF GREEK FUEL MARKET

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Keywords: Semi-supervised learning, network theory, fraud detection, anomaly detection.

Fraud detection in public revenue is considered one of the most important issues for tax authorities worldwide, since huge economic losses are attributed to the fraud of tax evasion alone, estimated up to €1 trillion, as stated by the European Commission. This paper introduces a novel graph-informed semi-supervised classification framework for fraud detection in the fuel market using unique administrative data from the Independent Authority for Public Revenue in Greece. In this work, we address the challenge of limited and noisy fraud labels by integrating quantitative covariate information, which is collected via the advanced inflow-outflow monitoring system at gas stations, with qualitative network data that capture multifaceted interactions among businesses. We model these interactions as a multiplex network and apply Tucker decomposition, to extract latent features, thus enriching the feature space available for fraud prediction.

To alleviate the intrinsic imbalance between fraud and non-fraud cases and partly conquer the limitation of fully supervised learning when labels are extremely scarce, having in our disposal only 0.28% of the gas stations that had been audited and found fraudulent and the remaining being unlabeled, we adopt the Positive-Unlabeled (PU) learning paradigm. Concretely, our approach is based on an iterative AdaSampling algorithm that dynamically adjusts the training process by reweighting the instances with respect to their misclassification probabilities. Simulation studies demonstrate that our graph-informed methods yield a marked improvement in sensitivity over traditional state-of-the-art classifiers, such as XGBoost, without a great loss in specificity. Real data experiments on Greek gas station audits also show that the incorporation of network-derived features significantly enhances fraud detection and provides a practical tool for more efficient use of audit resources.

The result indicated that the combination of sophisticated machine learning techniques with network information enhanced not only the predictive performance with respect to the problem at hand but also promised improved techniques in targeting and cutting costs within the public revenue systems when performing fraud investigations.

NETWORK-INFORMED BAYESIAN ANOMALY DETECTION BY USING GAUSSIAN PROCESSES

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Keywords: Bayesian, binary data, classification, fraud detection, Gaussian process, network, weak labeling.

Anomaly detection is a fundamental problem in data analysis, focusing on identifying instances that significantly deviate from expected behavioral patterns. It plays an essential role in various domains, from biology, where it helps in detecting rare genetic variations, to the financial sector, where it aims in uncovering fraudulent transactions. In financial applications, anomalies often correspond to illegal activities, such as tax evasion or financial fraud, making their accurate identification both an economic and a legal necessity. A particularly complex setting where anomaly detection is critical is the monitoring of fuel stations. Fraud in fuel sales, such as tax evasion or the manipulation of reported transactions, has substantial economic repercussions for governments and regulatory authorities. Therefore, designing effective methodologies for identifying such irregularities is of significant practical value. A common approach to anomaly detection is to formulate it as a binary classification problem, where each instance is labeled as either anomalous or normal. However, in real-world applications, and especially in financial fraud detection, the available information is typically derived from multiple sources. Specifically, data often include both entity-specific attributes, such as financial and operational characteristics of businesses, and network structures (e.g., transactions, shared members) that describe interactions between entities. This network representation can provide valuable information, revealing patterns that covariate analysis alone might miss, as fraudulent actors tend to exhibit distinct connectivity patterns compared to legitimate ones. In this study, we propose a probabilistic classification model that systematically integrates both types of information, based on recent advances in Bayesian machine learning and network modeling.

Our methodology is based on a binary Gaussian process classification model that simultaneously accounts for individual-level features and network-driven dependencies, allowing for a more comprehensive approach to fraud detection, enhancing the ability to detect and prevent fraudulent activities. Gaussian processes (GPs) provide a flexible nonparametric framework for capturing complex relationships while offering well-calibrated uncertainty estimates. Within the Bayesian paradigm, we estimate both model parameters and latent variables in a manner that fully accounts for uncertainty. The covariance structure of the GP is designed to incorporate two complementary types of similarity: one derived from entity-specific attributes and another reflecting the network-based dependencies between entities. By leveraging a combination of radial basis function (RBF) kernels and graph-based Laplacian

structures (Borovitskiy et al., 2021), our model effectively integrates heterogeneous sources of information, leading to improved predictive performance. Furthermore, a distinguishing aspect of our approach is the use of multiplex networks, which allow for a richer representation of relational information. Unlike single-layer networks, where connections between entities are captured through a single type of relationship, multiplex networks accommodate multiple layers of connectivity. This is particularly relevant in financial and business contexts, where interactions between entities are often multi-dimensional. The proposed framework adopts a product-of-experts formulation, where each layer of the multiplex network contributes to the model through a Laplacian-based representation. This allows us to effectively combine information across multiple network layers while maintaining a principled probabilistic structure. Moreover, we introduce a regularization mechanism that mitigates the effects of noisy or incomplete network information, enhancing the model’s generalization capabilities. To sample from the posterior, we use the first gradient marginal Metropolis-Hastings samplers introduced by Titsias and Papaspiliopoulos (2018), which is well-suited for Bayesian GPs. This approach ensures computational efficiency while maintaining robustness in parameter estimation.

In many real-world anomaly detection tasks, acquiring fully labeled datasets is difficult. Frequently, labels that identify fraudulent cases are weakly supervised, meaning they may be incomplete or uncertain. This issue is particularly relevant in financial fraud detection, where only a small fraction of cases are confirmed as fraudulent, while most data points remain unlabeled or ambiguous. To address this challenge, we incorporate weak supervision into our Bayesian framework, enabling the model to learn informative patterns even in the presence of noisy labels. We validate the proposed methodology through an extensive simulation study, examining its ability to detect anomalies under varying network structures and degrees of covariate informativeness. Furthermore, we apply our model to real-world data from fuel stations, demonstrating its effectiveness in detecting suspicious financial activities. Our results highlight the benefits of jointly modeling entity-level attributes and relational structures, particularly in cases where network connections provide strong predictive signals.

Overall, this work contributes to the field of anomaly detection by introducing a Bayesian GP classification model that integrates structured covariate information with multiplex network dependencies. By incorporating weak labeling, the approach is well-suited for real-world applications where fully labeled datasets are unavailable. Our empirical application to fraud detection in fuel stations illustrates the practical relevance of the model, offering insights that can inform regulatory policies and enforcement strategies. Future directions include extending the model to dynamic network settings, incorporating additional sources of domain knowledge to enhance interpretability and detection accuracy, and exploring alternative inference strategies to further improve computational efficiency.

References

Borovitskiy, V., Azangulov, I., Terenin, A., Mostowsky, P., Deisenroth, M., and Durrande, N. (2021), “Matérn Gaussian processes on graphs”, In International Conference on Artificial Intelligence and Statistics, 2593-2601, PMRL.

Titsias, M. K., and Papaspiliopoulos, O. (2018), “Auxiliary gradient-based sampling algorithms”, *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 80(4), pp. 749-767.

A LOCAL CLUSTERING APPROACH TO COLLECTIVE ANOMALY DETECTION VIA WEIGHTED PROPAGATION: THE CASE OF VAT FRAUD

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Keywords: Economic fraud, machine learning, VAT networks, anomaly clustering algorithm.

Collective fraud constitutes a critical challenge in the financial sector, as it involves groups of entities hiding illegal activities among many legitimate transactions. This concealment strategy becomes even more complex as the types of collective fraud vary, creating diverse patterns in the transaction networks. Traditional fraud detection methods primarily highlight individual entities with suspicious characteristics, while community detection approaches often fail to uncover well-organized collective fraud schemes involving small, tightly connected groups of entities. In this work, we propose a novel weighted propagation-based fraud detection method that takes advantage of business-specific covariates and transactional or membership networks. Our approach begins with one or more seed nodes (initial suspects) and systematically explores their connections, including higher-order subnetworks, selecting nodes with suspicious characteristics or interactions. The result is a compact, information-rich local graph partition centered on the seed nodes, designed to uncover meaningful clustering structures indicative of collective fraud. An simulation study evaluates the proposed methodology against standard alternatives in scenarios involving collective fraud within large-scale datasets. Furthermore, a real-data application, using data from the Greek economy, demonstrates the practical utility of the method in detecting collective fraud schemes.

Session C1

**AI, LEADERSHIP AND
ORGANIZATIONAL CHANGE**

**Chair: Irene Nikandrou, Athens University of Economics and Business,
Greece**

AI AND THE FUTURE OF LEADER IDENTITY: TWO THOUGHT EXPERIMENTS

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Keywords: Artificial intelligence, Thought experiment, Leader identity.

Artificial Intelligence (AI) is increasingly moving from a subordinate tool to an autonomous actor in organizational settings (Wilson & Daugherty, 2018). On the other hand, leader identity and identity leadership (Haslam et al., 2022) are topics of importance and interest in management (Sveningsson & Alvesson, 2003) and leadership (Epitropaki et al., 2017). In this paper we explore the question: If AI agents acquire significant degree of efficacy and autonomy, and if they (a) act as self-governed team members or (b) are placed in positions of leadership, how should we rethink established notions of leader identity?

Thought experiments provide a conceptual lens for analyzing phenomena lacking empirical documentation (Aguinis et. al., 2023; Cornelissen & Durand, 2014; Introna & Whitley, 1997; Kornberger & Mantere, 2020) and have been applied in areas such as entrepreneurship (Sarasvathi, 2001), supply chain management (Bille, 2024), and trust (Folger & Turillo, 1999). Thought experiments begin by asking “what if” something were to occur and proceed to test the boundaries of existing theories in radically new contexts (Bankins & Formosa, 2020). By constructing two imagined but plausible scenarios we illuminate potential theoretical and practical implications which are already entering the public discourse and to which we have no empirical access.

In the first thought experiment – the Leader Displacement Dilemma – Lila, a proven human leader in a disaster response agency, oversees a team of humans and autonomous AI agents responsible for coordinating evacuations during emergencies. AI agents are equipped with advanced decision-making capabilities. During a catastrophic flood, Ares, the most advanced AI system in the team, defies Lila’s cautious evacuation plan and implements a riskier alternative. Ares’ decision succeeds, saves hundreds of lives and earns widespread acclaim. Human responders begin to defer to Ares for critical inputs, while Lila struggles to reassert her leadership and rebuild team cohesion. Key boundary conditions include: (a) AI autonomy, (b) team norms that allow members’ initiative (e.g., psychological safety; Edmondson, 2003), and (c) flat and informal hierarchical structure.

In the second thought experiment – the Co-Leadership Dilemma – Sharon, a seasoned human leader known for her domain expertise, is assigned to co-lead an innovation team with Elara – an advanced AI agent formally endorsed by the organization. A moment of tension arises when Elara presents a data-backed strategic pivot that contradicts Sharon’s plan. Some team members align with Elara’s precision and impartiality, while others rally around Sharon’s human-centered perspective. Key boundary conditions include (a) organizational structures that legitimize AI leadership, (b) team norms that tolerate non-human co-leaders, and (c) recognition of Elara’s empathy as artificial yet sufficiently persuasive.

According to Gecas (1982), individuals derive self-concept from the roles they occupy, relying on expertise, charisma, or authority. In the Co-Leadership Dilemma, Elara's superior analytics and "empathic listening" challenge Sharon's core leadership competencies. This displacement spurs role conflict and ambiguity (Ebbers & Wijnberg, 2017). Similarly, Ares' advanced data-processing capacity and absence of emotion-driven risk aversion challenge Lila's judgment and destabilize her self-concept as a leader. What is the basis of her leadership role: technical expertise, relational engagement, or symbolic representation? How will the emergence of autonomous AI agents as leaders or team members affect the stages of noticing, interpreting, authoring and enacting (Hammond et. al., 2017) of a leader identity?

From a constructivist perspective (DeRue & Ashford, 2010), leadership emerges as a process of reciprocal claiming and granting of legitimacy. In the Leader Displacement Dilemma, Ares bypasses Lila's claim to leadership and spreads doubt among the human members. Is a "non-grant" by an AI agent equivalent to a "non-grant" by a human team member? Moreover, how does the perceived objectivity or technological superiority of an AI amplify or diminish its role in shaping team perceptions of leadership? How might constructivist theories account for the unique characteristics of AI agency and autonomy in team interactions? In the second thought experiment, enough team members willingly grant the leader role to Elara as the latter claims it with robust data, rational arguments, and even empathic feedback. Sharon, as a reaction, leans on her interpersonal abilities to accumulate social capital. Is authenticity an obstacle to leader legitimacy when empathy and ethical reasoning can be algorithmically simulated?

According to social identity theory (Hogg, 2001) leader identity develops as leaders embody group prototypicality—their ability to represent and advance the group's norms and interests (Haslam et al., 2022). In the Leader Displacement Dilemma, Lila's authority is undermined as Ares positions itself as a superior representative of the group's goals. Furthermore, this displacement challenges the team's collective identity, rooted in shared human experiences, emotional connections, and values. How might collective identity extend to include AI agents? Can Lila reassert her leadership by steering her team toward a more inclusive conception of leadership that integrates human and AI initiative? In the second thought experiment, the team fragments into subgroups favoring Sharon or Elara, driven partly by members' belief in the reliability of data versus the value of human insight. As autonomous AI enters leadership circles, should we expect such splintering of group identity and will the AI be able to not only represent but also advance and steer the collective identity over time?

These three perspectives begin to shed some light on how future autonomous AI might simultaneously disrupt leader's role identity, reconfigure social constructions of how leaders see themselves in the "social mirror", and scatter group prototypicality. Role identity theory highlights human leaders' internal struggle, social constructivism underscores the external processes of claiming/granting legitimacy, and social identity theory reveals how team identity may shift depending on differential acceptance of AI versus human legitimacy as leader or member.

By challenging either/or approaches to the future of human versus AI leadership (Van Quaquebeke & Gerpott, 2023), these thought experiments imagine a fictional

reshaping (Dries et. al., 2024) of leader identity as AI potentially achieves greater autonomy. We offer this approach as a provocative starting point for further problematization of the future of leader identity. Can AI develop their own – identifiable and accepted – leader identity? How might human leaders redefine their identity to remain relevant?

References

- Aguinis, H., Beltran, J. R., Archibold, E. E., Jean, E. L., & Rice, D. B. (2023). Thought experiments: Review and recommendations. *Journal of Organizational Behavior*, 44(3), 544-560.
- Bankins, S., & Formosa, P. (2020). When AI meets PC: Exploring the implications of workplace social robots and a human-robot psychological contract. *European Journal of Work and Organizational Psychology*, 29(2), 215-229.
- Bille, Amanda. 2024. "Learning from Habermas and Machiavelli: a thought experiment in supply chain management". *International Journal of Logistics Management*. <https://doi.org/10.1108/ijlm-08-2023-0312>
- Cornelissen, J. and Durand, Rodolphe. 2014. "Moving Forward: Developing Theoretical Contributions in Management Studies". None.
- DeRue, D. S., & Ashford, S. J. (2010). Who will lead and who will follow? *Academy of Management Review*, 35(4), 627–647.
- Dries, N., Luyckx, J., & Rogiers, P. (2024). Imagining the (distant) future of work. *Academy of Management Discoveries*, 10(3), 319-350.
- Ebbers, J. J., & Wijnberg, N. M. (2017). Betwixt and between: Role conflict, role ambiguity and role definition in project-based dual-leadership structures. *Human relations*, 70(11), 1342-1365.
- Edmondson, A. C. (2003). Speaking up in the operating room: How team Leaders Promote learning in interdisciplinary action Teams. *Journal of Management Studies*, 40(6), 1419–1452.
- Epitropaki, O., Kark, R., Mainemelis, C., & Lord, R. G. (2017). Leadership and followership identity processes: A multilevel review. *The Leadership Quarterly*, 28(1), 104–129.
- Folger, R., & Turillo, C. J. (1999). Theorizing as the thickness of thin abstraction. *The Academy of Management Review*, 24, 742–758.
- Gecas, V. (1982). The self-concept. *Annual Review of Sociology*, 8(1), 1–33.
- Haslam, S. A., Gaffney, A. M., Hogg, M. A., Rast III, D. E., & Steffens, N. K. (2022). Reconciling identity leadership and leader identity: A dual-identity framework. *The Leadership Quarterly*, 33(4), 101620.
- Haslam, S. A., Reicher, S. D., & Platow, M. J. (2020). *The new psychology of leadership: Identity, influence and power*. Routledge.
- Hogg, M. A. (2001). A social identity theory of leadership. *Personality and Social Psychology Review*, 5(3), 184–200.
- Introna, L., & Whitley, E. (1997). Imagine: Thought experiments in IS research. In A. S. Lee, et al. (Ed.), *Information systems & qualitative research* (pp. 481–496). Boston: Springer.
- Kornberger, M & Mantere, S 2020, 'Thought experiments and philosophy in organizational research', *Organization Theory*, vol. 1, no. 3.

Sarasvathy, S. D. (2001). Causation and effectuation. *The Academy of Management Review*, 26, 243– 263.

Sveningsson, S., & Alvesson, M. (2003). Managing managerial identities: Organizational fragmentation, discourse and identity struggle. *Human Relations*, 56(10), 1163–1193.

Van Quaquebeke, N., & Gerpott, F. H. (2023). The now, new, and next of digital leadership: How Artificial Intelligence (AI) will take over and change leadership as we know it. *Journal of Leadership & Organizational Studies*, 30(3), 265-275.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, 96(4), 114–123.

MOBILIZING EMPLOYEES TO COMMIT TO A DIGITALLY TRANSFORMED ORGANIZATION

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Keywords: Digital transformation, top management, middle managers, employees.

Many organizations choose to transition to a digital era via a digital transformation process; a strategic decision taken by top management. Digital transformation is a process encompassing multiple stages (Vial, 2019) that require the activation and participation of every internal and external stakeholder. Focusing on the internal stakeholders that might define digital transformation success, the role of managers, middle managers, and employees should be highlighted and explored. On one hand, there are top management and middle managers who are leading digital transformation efforts and on the other hand, there are employees who are asked to follow the strategic decision and adopt new technologies. Employee participation influences the successful outcome of a digital-orientated strategic change (Butschan et al., 2019; Vereycken et al., 2021). Their positive impact on the successful adoption of any digital initiative exceeds other related parameters like technology use, country level, and firm size (Vereycken et al., 2021).

Mobilizing employees to pursue a digitally transformed organization is a leadership issue as top management and middle managers are advocates of the digital future. Starting from top management, given it is a strategic decision, it is noticed that managerial change capabilities shift organization behavior towards change (Bendig et al., 2022) underlining the importance of management commitment from the early stages of digital transformation when the need to understand and formulate a strategy is highly significant (Sommer, 2019). Their commitment and supportive leadership will activate and convince employees in different hierarchical levels to follow this strategy and disseminate it (Horvath & Szabo, 2019). Onboarding lower-level managers like middle managers is important as they have a more personal, direct, and close relationship with employees that influences the progress of any technology adoption (Bäckström & Lindberg, 2019).

An important question that arises is how leadership can mobilize employees to participate in digitally transforming the organization. To try to answer this multi-faced question this work will focus on middle managers and employees due to the great influence that both stakeholders have for implementing a successful outcome. More specifically, resting on a theoretical background, it will focus on leadership decisions that facilitate the middle manager's involvement and aid employee commitment.

Middle managers have a unique point of view that is shaped by each department's goals, and personal opinions about the transformation process (Holmlund et al., 2017). This means that if they don't have a clear picture and understanding of digital transformation objectives may not be able to communicate the new strategic shift towards digital transformation. Therefore, top management's responsibility is to cultivate an encouraging and inclusive environment that supports middle manager's

participation and involvement (Gfrerer et al., 2020; Su et al., 2023). This could be achieved by involving middle managers throughout the digital transformation process or by keeping them updated about the digital transformation decisions and requesting their feedback (Gfrerer et al., 2020).

Simultaneously, top management should handle the conflicts between middle managers driven by each manager's efforts to fulfill their team goals. To overcome this obstacle, top management may promote cross-departmental collaborations to cultivate collaboration and communication (Su et al., 2023). Another important aspect that will facilitate employee participation in any technology adoption is determining employee digital competencies level. Acknowledging existing digital competencies level could only simplify the implementation process as the organization will forecast shortcomings. During transformation, employees are asked to adopt new technologies that require designing reskilling activities to enhance existing levels (Lauterbach et al., 2020; Schlegel & Kraus, 2021). The high competencies level is a digital transformation facilitator that offers top management more freedom to formulate a more flexible implementation plan to achieve better performance rates not only in usage but also at the organization level (Butschan et al., 2019). Additionally, understanding the competencies level could let leadership actively involve employees in digital transformation process like participating in meetings with technology providers to determine the new technological requirements. This active participation supports communication efforts and cultivates an encompassing environment that benefits the implementation process (Pachni Tsitiridou, 2024).

Except for active participation, employees can be mobilized through multiple initiatives as the digital transformation process unfolds. Creating supportive structures that aid employees during technological transition is an indirect way that leadership can exploit. The supportive structures can create a feeling of continuity and alignment inside the organization (Hess et al., 2016) that could trigger participation. Additionally, these complementary or new supportive structures such as departments, functions, processes, etc. allow a successful technological transition (Taylor & Helfat, 2009). Another initiative that requires leadership support is the creation of cross-functional structures as they signal new collaborations between the departments (Özkan Özen & Kazançoğlu, 2021) and create new communication paths that could foster innovation and creativity. However, it is noticed that cross-functional teams are limited by organizational human resources and are unable to create cross-functional structures because they set in danger the organizations proper function. On the other hand, organizations with specialized structures/departments are unable to proceed with initiative as different skills are required (Pachni Tsitiridou, 2024). In these cases, leadership intervention is required to pivot and propose innovative solutions that facilitate digital transformation.

Leadership and more specifically top managers are obligated to foster a supportive environment, engaging middle managers and motivating employee participation to ensure a successful transition to the digital era. Considering organizational abilities and needs they can formulate an implementation plan including initiatives that firstly will support employees during the transition and secondly will encourage collaboration, innovation, and participation. Additionally, middle managers represent an intermediary that drives employee participation and ensures the successful

implementation of digital initiatives. All the proposed implementation initiatives supported by middle managers can enhance collaboration and cultivate an innovative mindset. A well-coordinated digital transformation leadership in all hierarchical levels will increase the chances for a successful digital transformation outcome.

Future research should explore the long-term impact that continued learning and training programs have on organizations' digital transformation efforts, and employee motivation. The learning opportunities provided by AI advancements like AI-driven adaptive training and learning paths create opportunities to examine their impact on employee engagement and digital competency. Another promising research avenue is the investigation of different leadership styles to mobilize middle managers and employees to accelerate the digital transformation process. Additionally, comparing different transformation leadership styles to determine which styles can motivate employees and generate successful outcomes could be a future study. Considering the pivotal role of middle managers future research should investigate their specific competencies and leadership behaviors to effectively bridge and successfully translate the top management strategies to employees. Middle managers' actions are complemented by elements like personal incentives, absorptive capability, and corporate governance. Exploring the interaction between these elements and middle managers might provide a deeper understanding of their stand on digital transformation initiatives. More light should be shed on understanding the influence that middle managers have on digital transformation and its specific aspects such as digital adoption. This understanding will let top management develop better-supporting mechanisms for them that will accelerate implementation.

References

- Bäckström, I., & Lindberg, M. (2019). Varying involvement in digitally enhanced employee-driven innovation. *European Journal of Innovation Management*, 22(3), 524–540. <https://doi.org/10.1108/EJIM-01-2018-0008>
- Bendig, D., Wagner, R., Jung, C., & Nüesch, S. (2022). When and why technology leadership enters the C-suite: An antecedents perspective on CIO presence. *The Journal of Strategic Information Systems*, 31(1), 101705. <https://doi.org/https://doi.org/10.1016/j.jsis.2022.101705>
- Butschan, J., Heidenreich, S., Weber, B., & Kraemer, T. (2019). Tackling Hurdles to Digital Transformation - The Role of Competencies for Successful Industrial Internet Of Things (IIoT) Implementation. *International Journal of Innovation Management*, 23(4). <https://doi.org/10.1142/S1363919619500361>
- Gfrerer, A., Hutter, K., Füller, J., & Ströhle, T. (2020). Ready or Not: Managers' and Employees' Different Perceptions of Digital Readiness. *California Management Review*, 63(2), 23–48. <https://doi.org/10.1177/0008125620977487>
- Hess, T., Benlian, A., Matt, C., & Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, 15(2), 123–139. <https://doi.org/10.4324/9780429286797-7>
- Holmlund, M., Strandvik, T., & Lähteenmäki, I. (2017). Digitalization challenging institutional logic. *Journal of Service Theory and Practice*, 27(1), 219–236. <https://doi.org/10.1108/JSTP-12-2015-0256>
- Horvath, D., & Szabo, R. Z. (2019). Driving forces and barriers of Industry

4.0: Do multinational and small and medium-sized companies have equal opportunities? *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, 146, 119–132. <https://doi.org/10.1016/j.techfore.2019.05.021>

Lauterbach, J., Mueller, B., Kahrau, F., & Maedche, A. (2020). Achieving Effective Use When Digitalizing Work: The Role of Representational Complexity. *MIS Q.*, 44.

Özkan Özen, Y., & Kazançoğlu, Y. (2021). Analysing workforce development challenges in the Industry 4.0. *International Journal of Manpower*, ahead-of-p. <https://doi.org/10.1108/IJM-03-2021-0167>

Pachni Tsitiridou, O. (2024). Digital transformation and organizational impact [University of Macedonia, School of Information Sciences]. <https://doi.org/10.12681/eadd/56327>

Schlegel, D., & Kraus, P. (2021). Skills and competencies for digital transformation – a critical analysis in the context of robotic process automation. *International Journal of Organizational Analysis*, ahead-of-p. <https://doi.org/10.1108/IJOA-04-2021-2707>

Sommer, A. F. (2019). Agile Transformation at LEGO Group. *Research-Technology Management*, 62(5), 20–29. <https://doi.org/10.1080/08956308.2019.1638486>

Su, F., Mao, J.-Y., & Jarvenpaa, S. L. (2023). Organizational path transformation in response to disruptive environmental changes: The role of middle managers. *Long Range Planning*, 56(2), 102292. <https://doi.org/https://doi.org/10.1016/j.lrp.2022.102292>

Taylor, A., & Helfat, C. E. (2009). Organizational Linkages for Surviving Technological Change: Complementary Assets, Middle Management, and Ambidexterity. *Organization Science*, 20(4), 718–739.

Vereycken, Y., Ramioul, M., Desiere, S., & Bal, M. (2021). Human resource practices accompanying industry 4.0 in European manufacturing industry. *Journal of Manufacturing Technology Management*, 32(5), 1016–1036. <https://doi.org/10.1108/JMTM-08-2020-0331>

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, 28(2), 118–144. <https://doi.org/https://doi.org/10.1016/j.jsis.2019.01.003>

RETHINKING LEADERSHIP IN THE DIGITAL AGE: THE CONVERGENCE OF AI, VIRTUAL COLLABORATION AND SHARED LEADERSHIP

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Keywords: Shared leadership, digital age, AI, virtual teams.

Introduction

The increasing prevalence of virtual teams, particularly following the COVID-19 pandemic, has driven organizations to rethink leadership models (Schmidt & Van Dellen, 2022). Traditional hierarchical leadership structures are often inadequate for remote and hybrid work environments, necessitating alternative approaches. At the same time, artificial intelligence (AI) serves as a valuable co-leader by enhancing decision-making through data analysis and predictive capabilities (Peifer et al., 2022). This study investigates how technological advancements, such as digital platforms and AI, shape contemporary leadership practices. Specifically, it explores the effectiveness of shared leadership in virtual environments and the role of technology in facilitating leadership distribution (Han & Hazard, 2022), while discussing how digital platforms and AI serve as co-leaders, replacing traditional leadership roles and creating the need to develop new technology leadership skills.

Theoretical background

A systematic literature review synthesizes research on shared leadership in virtual teams and co-leadership through digital platforms and AI. It integrates findings on leadership substitutes, digital collaboration, and shared leadership in virtual teams, addressing space and place leadership (Schmidt & Van Dellen, 2022), the role of virtual platforms (Schwarz, 2015), and digital coordination mechanisms (Nordbäck & Espinosa, 2019). Shared leadership enhances virtual team effectiveness through autonomy, collaboration, and accountability (Muethel & Hoegl, 2010), but depends on structured coordination mechanisms. High power-distance teams often struggle with shared leadership, while low power-distance teams adapt more readily (Nordbäck & Espinosa, 2019). Trust is critical for enabling shared leadership, facilitating communication and initiative-taking (Castellano et al., 2021). Digital tools improve leadership alignment, but overreliance can create ambiguity (Newman & Ford, 2021). AI introduces new leadership dynamics, requiring data literacy, AI-based problem-solving, and human-AI collaboration (Peifer et al., 2022). Without structured integration, AI can create ambiguity in decision-making. Organizational culture plays a key role in facilitating trust in AI and aligning its capabilities with human leadership strengths.

Findings

The study proposes a conceptual model capturing the interplay between contextual factors, technological developments, and shared leadership mechanisms in virtual teams. It shows how virtual work environments and organizational culture interact with digital tools and AI as active co-leaders, influencing coordination mechanisms

such as trust, distributed task management, and relational role alignment. Structured leadership processes and digital competencies are emphasized as foundational for effective shared leadership.

Practical implications

To maximize shared leadership benefits, organizations must establish structured coordination strategies, integrate digital tools and AI, and balance leadership distribution. Effective coordination requires implicit mechanisms like shared mental models and explicit strategies like leadership rotations and check-ins (Nordbäck & Espinosa, 2019). Digital collaboration tools support knowledge exchange and decision-making transparency (Schwarz, 2015). Leaders and teams must develop data literacy and human-AI collaboration skills. Trust-building initiatives are essential for smooth leadership transitions and collective accountability (Castellano et al., 2021).

Originality/Value

This study clarifies contradictions in shared leadership research, showing that effectiveness depends on structured coordination rather than mere decentralization. It identifies key enablers and challenges, offering practical guidance for organizations undergoing digital transformation. The research highlights the need for ethical AI guidelines, structured leadership adaptation, and AI-human collaboration models. Future research should examine how AI can further optimize leadership functions in remote environments while preserving human oversight (Newman & Ford, 2021; Peifer et al., 2022).

References

- Carte, T.A., Chidambaram, L. & Becker, A., 2006. Emergent leadership in self-managed virtual teams: A longitudinal study of concentrated and shared leadership behaviors. *Group Decision and Negotiation*, 15, pp.323–343.
- Castellano, S., Chandavimol, K., Khelladi, I. & Orhan, M.A., 2021. Impact of self-leadership and shared leadership on the performance of virtual R&D teams. *Journal of Business Research*, 128, pp.578–586.
- Han, S.J. & Hazard, N., 2022. Shared leadership in virtual teams at work: practical strategies and research suggestions for human resource development. *Human Resource Development Review*, 21(3), pp.300–323.
- Hoegl, M. & Muethel, M., 2016. Enabling shared leadership in virtual project teams: A practitioners' guide. *Project Management Journal*, 47(1), pp.7–12.
- Mayer, C., Sivatheerthan, T., Mütze-Niewöhner, S. & Nitsch, V., 2023. Sharing leadership behaviors in virtual teams: effects of shared leadership behaviors on team member satisfaction and productivity. *Team Performance Management*, 29(1/2), pp.90–112.
- Muethel, M. & Hoegl, M., 2010. Cultural and societal influences on shared leadership in globally dispersed teams. *Journal of International Management*, 16(3), pp.234–246.
- Newman, S.A. & Ford, R.C., 2021. Five steps to leading your team in the virtual COVID-19 workplace. *Organizational Dynamics*, 50(1), p.100802.
- Nordbäck, E.S. & Espinosa, J.A., 2019. Effective coordination of shared leader-

ship in global virtual teams. *Journal of Management Information Systems*, 36(1), pp.321–350.

Peifer, Y., Jeske, T. & Hille, S., 2022. Artificial intelligence and its impact on leaders and leadership. *Procedia Computer Science*, 200, pp.1024–1030.

Schmidt, G.B. & Van Dellen, S.A., 2022. Leadership of place in virtual environments. *Leadership*, 18(1), pp.186–202.

Schwarz, V.R., 2015. Building a community in the gig economy. Available at: <https://medium.com/@VRavivSchwarz/building-a-community-in-the-gig-economy-a082285a0f04>.

IS HIGHER EDUCATION MEETING THE REQUIREMENTS OF THE NEW PROFESSIONS LINKED TO A.I. AND DATA?

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Keywords: Job market, higher education, artificial intelligence, data science, text mining, NLP, IS education, skills, requirements, competencies.

Abstract

The advent of Artificial Intelligence (AI) is bringing about far-reaching changes, particularly in terms of the emergence of new professions. These technologies are creating a need for new, specific skills, particularly in the area of data. The aim of this study is to identify the skills-requirement gaps between the higher education courses that prepare students in the fields of AI and Data, and the needs of the job market. We leverage text mining approach and compare the offerings of curricula in the field of AI and Data (manually collected), from the websites of higher education establishments in France and with offers in the job market in France (automatically extracted via online job portals). Our analysis categorizes the most sought-after skills in AI-related job offers into three main groups: technical skills, cross-disciplinary skills, and interdisciplinary skills. We also find that the extent of the skills-requirements gap is rather large, implying an unmet need in society. These findings extend emerging research in AI competencies and IS education as well as better inform national policymakers on the nature of the skills-requirements gap that needs urgent bridging in the context of AI policies. The research also offers other insights that can be used by higher education institutions to better shape training programs to meet the demands of the growing AI and data job market in France.

Session D1

SUSTAINABILITY AND DIGITAL TRANSFORMATION: LEVERAGING AI FOR ENVIRONMENTAL IMPACT A Panel Roundtable Discussion

**Chair: Phoebe Koundouri, Athens University of Economics and
Business, Greece**

SUSTAINABILITY AND DIGITAL TRANSFORMATION: LEVERAGING AI FOR ENVIRONMENTAL IMPACT

A Panel Roundtable Discussion

Moderator:

- **Dr. Phoebe Koundouri**, Professor at the Athens University of Economics and Business, Founder and Director of AE4RIA, an alliance promoting research and innovation for sustainable development, aligning with UN SDGs and European initiatives. Dr. Koundouri's expertise lies in sustainable development, environmental policy, and AI applications in sustainability.

Panel members:

1. **Dr. Alberto Naveira Garabato**, Professor in Physical Oceanography at the University of Southampton. His research on instabilities and mixing has been fundamental to understanding and quantifying the ocean's role in the Earth climate system.
2. **Dr. Ali Mashayek**, Associate Professor of Climate Dynamics in the Department of Earth Sciences at the University of Cambridge, specializing in the physical and biological processes in the ocean that are central to its role in regulating the climate system across a wide range of timescales.
3. **Dr. Anthony Papavasiliou**, Assistant Professor at the National Technical University of Athens. His research interests focus on operations research, electricity market design, and power system operations.
4. **Dr. Fivos Papadimitriou**, Researcher at the Athens University of Economics and Business & AE4RIA. His expertise lies in the creation of original and innovative mathematical methods and models for the measurement of spatial complexity, spatial entropy and landscape complexity.

Abstract:

The convergence of artificial intelligence (AI) and sustainability presents a pivotal opportunity to address pressing environmental challenges while driving business innovation. This session, organized by AE4RIA, explores the transformative potential of AI and data analytics in advancing sustainable practices across industries and reshaping environmental stewardship in the digital era.

Digital technologies are revolutionizing how organizations approach sustainability – from AI-powered climate modeling and predictive analytics for environmental risk assessment to smart resource management systems and automated environmental monitoring.

Our distinguished speakers will examine how organizations can effectively harness AI and data analytics to enhance their sustainability initiatives while managing associated challenges. Topics such as the integration of AI systems for environmental monitoring and resource optimization, data-driven approaches to measuring and reducing environmental impact, and balancing the energy demands of AI infrastructure with sustainability goals will be discussed.

The session will feature case studies highlighting successful implementations of AI-driven sustainability initiatives, followed by a discussion on future trends and opportunities at the intersection of digital technology and environmental stewardship. Participants will gain practical insights into leveraging AI for sustainability while understanding the critical leadership considerations in driving environmentally responsible digital transformation.

Session A2

**INCLUSION, DIVERSITY AND AI
ETHICS**

Chair: Dimitris Karlis, Athens University of Economics and Business,
Greece

DIVERSITY AND INCLUSION: AI's ROLE IN MANAGING NEURODIVERSITY

Nancy Papalexandris

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Keywords: Diversity, inclusion, neurodiversity, artificial intelligence.

Over the past 25 years starting with large multinationals, special policies and practices have been introduced to address the increasing diversity in the workforce and reduce inequalities and lack of opportunities for people belonging to less represented groups. Countries have introduced legislation against various forms of discrimination and International Organizations such as the United Nations have included in their 17 Sustainable Development Goals in 2015, Gender Equality (SDG 5), Decent Work and Economic Growth (SDG 8) and Reduced Inequalities (SDG 10).

International companies working in diverse environments and facing workforce complexities were the first to introducing DEI policies and practices as they gradually realized the benefits from hiring and promoting people from a larger talent pool and the advantages for innovation and out-of-the box thinking often provided by people from different backgrounds with different characteristics. Gradually, inclusion has been added to the picture which meant that not only hiring but also giving the opportunity to diverse people to participate in decision making and feel that they belong to their companies is needed (Roberson, 2006).

The main dimensions initially addressed by diversity programs were gender, race, and ethnic origin. This was the result of widespread discrimination which traditionally and apparently took place around these dimensions. To these, issues dealing with ageing, sexual orientation and special needs were gradually added (Farndale et al. 2015). People in these groups are facing different problems in the workplace and companies have encouraged the creation of special resource groups dealing with these issues where employees can join on a voluntary basis and propose solutions.

While less attention was given to special needs, apart from certain incentives to hire people with walking, hearing and seeing disabilities, it appears that changing demographic conditions and skill requirements has opened opportunities for a group of people falling within the spectrum of neurodiversity. Neurodiverse people are not disabled or mentally ill. They are people whose neurons are wired in a different way from that of neurotypical people. According to Bernick (2022) there is a sharp increase in the neurodiverse workforce which includes people with mild autism, Attention Deficit and Hyperactivity Disorder (ADHD), dyslexia, etc. Over the next decade as estimated by researchers from Drexel University, almost 1 million young people with autism will turn 18. The current unemployment rate among neurodivergent (ND) people is very high despite the fact that they often possess University Education and technical skills. The problem lies in the fact that they cannot meet standard interview requirements or display the human skills required by recruiters such as skills in communication, teamwork, decision making, leadership or even basic self-confidence. They often display great anxiety, nervousness and cannot keep eye contact. A number of articles examining this situation (Austin & Pisano, 2017), (Grandin, 2023), (Praslova, 2021) have been published on the subject stressing the

need for inclusion and the possible benefits from hiring employees with neurodiversity. It is recognized that NV people may possess apart from weaknesses some unique strengths. (Bewley, 2016) For example ADHD is linked to creativity and certain individuals with dyslexia possess excellent visual-spatial talents (Houdek, 2022).

Lately the challenges of ND can be addressed with solutions based on Artificial Intelligence (Keil & Ketzer 2024). AI-driven apps can help ND employees recognize tasks in messages, automatically transcribe live meeting notes, check messages for precision and completeness, transfer voice to text for those struggling with literacy, process information in order to prevent cognitive overload. Communication tools can help those with difficulty with in-person contacts or those preferring asynchronous communication. Time-tracking tools and focus enhancing tools can help in maintaining concentration and avoid distractions. A self-monitoring app can detect extra stress and suggest a break or offer a game for relaxation. Finally a pair of smart glasses can help persons with difficulty in reading facial cues identify emotions and improve their social skills. The range of available AI tools is constantly increasing and some can be very useful to neurotypical employee as well. Companies must identify those appropriate for each ND user's needs and skillsets. Given the above, this paper tried to identify the extent to which diversity and inclusion programs of companies operating in Greece have started addressing the case of neurodiversity and whether they are using available AI tools. More specifically this paper has tried the following:

1. Define the neurodiversity movement, how it emerged and the various disorders it includes
2. Present the role of AI in employing and supporting neurodivergent employees and the reasons for including them in their talent strategy.
3. Describe the assistance provided by intermediaries, NGOs and neurodiversity advocates as well as the adjustments required to accommodate them as documented in the international literature.
4. Present a general picture of the situation in Greece through a survey among HR practitioners and interviews with neurodiversity activists, health professionals and clinical psychologists.
5. Present three cases studies of international companies active in neurodiversity operating in Greece whose practices can serve of examples of best practices.
6. Present conclusions and plans for a more extensive survey of the situation among Greek firms.

From our research among HR practitioners some large MNCs in Greece are addressing the issue while the concept is still hardly known by most organizations. Interviews with diversity experts, neurodiversity advocates, and special needs educators showed the limited knowledge about this issue among the business community and the need for raising awareness through further research as well as the role of

HR in creating a culture of inclusion where neurodivergent talent can be accommodated. Raising staff sensitivity, inviting employees as volunteers, cooperating with nonprofits and inviting top management to embrace such initiatives were mentioned together with the importance of learning from successful practices and experiences of international companies operating in Greece which can serve as best practice examples. Undoubtedly the role of AI is of critical importance for companies wishing to create an inclusive work environment where all available talent will be offered the opportunity to succeed.

References

Austin, R. D. and Pisano, G.P. (2017). Neurodiversity as a Competitive Advantage, *Harvard Business Review*, May-June.

Bernick, M. (2023). Is Your Company Inclusive of Neurodivergent Employees? *Harvard Business Review*, February.

Bewley, H. and George, A. (2016). Neurodiversity at work. London: National Institute of Social and Economic Research, 1-68

Farndale, E., Biron, M., Briscoe, D. R., & Raghuram, S. (2015). A Global Perspective on Diversity and Inclusion in Work Organisations. *The International Journal of Human Resource Management*, 26, 677-687. <https://doi.org/10.1080/09585192.2014.991511>

Houdek, P. (2022). Neurodiversity in (not only) public organizations: an untapped opportunity? *Administration and Society*, 54(9), 1848-1871

Grantin, T. (2023). People with Different Kinds of Minds. When Great Minds don't think alike. *Harvard Business Review*, May.

Keil, MV and Ketzer, D. (2024). Neurodivergent Employees: AI's Role in New Work Challenges. MSM Online Academic Conference Presentation, University of Mannheim

Praslova, L. (2021). Autism doesn't hold people back at work. Discrimination does *Harvard Business Review*. December.

Roberson, Q.M. (2006). Disentangling the Meanings of Diversity and Inclusion in Organizations. *Group and Organization Management*, Vol. 31, No.2, April, 221-236.

INCLUSION IN ARTIFICIAL INTELLIGENCE: PERSPECTIVES FROM THE BUSINESS COMMUNITY AND THE PUBLIC

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Keywords: Artificial intelligence, diversity, equity, inclusion, fairness.

Like most major technological advancements, artificial intelligence (AI) has profound implications for all aspects of society (e.g. social, economic, political, health, learning, etc.) When it comes to inclusion, AI represents a double-edged sword with each iteration creating opportunities to foster inclusion while also posing challenges that must be addressed. For example, AI education technology promises to assist students with disadvantages in developing skills needed for success but only to the extent that students have access to it, something that is not largely the case even in locations where broadband access is otherwise high (Eden et. al, 2024; D'Agostino, 2023). Similarly, AI also offers opportunities to advance financial inclusion by potentially providing better ways to manage credit risks, reduce fraud and create credit scores, amongst other things. At the same time, it is potentially exacerbating problems that include ensuring access for people with disabilities and from other vulnerable communities and or overcoming inherent biases built into AI algorithms (Ozili, 2021). There is a compelling case to be made as well, for how AI can significantly expand access to medical and mental health care. For instance, the World Health Organization (2021) reported that there is a substantial shortage of mental health professionals, especially in low- and middle-income countries. AI chatbots can help bridge this gap by offering support to those without access to mental health care (Petracek, 2024). However, for this inclusive potential to be realized a number of concerns and challenges need to be addressed. They include data privacy considerations and the inability of AI to offer the level of empathy and emotional support that is necessary to deal with many mental health needs (Miner, Milstein, and Hancock, 2017). Issues regarding inclusion also extend to the AI development community where there are consistent calls for increasing the share of women and minorities in AI research and industries (West et al., 2019; Cachat-Rosset & Klarsfeldb, 2025).

At the same time, the above discussion is not intended to suggest, that AI professionals are indifferent to inclusion related concerns and challenges. In their review of AI ethical guidelines Cachat-Rosset & Klarsfeldb (2025) reported that diversity, equity and inclusion (DEI) principles were reflected in 76% of the guidelines they reviewed. However, they also reported that they found no document, code or charter specifically dedicated to DEI. Instead, they found that such principles were always embedded within more global ethical principles for AI.

Clearly for AI to realize its transformative potential, concerns for inclusion need to remain front and center. This paper aims to contribute to our understanding of

how inclusion is being taken into consideration when it comes to AI development and implementation. First, we report on insights that emerged from a four-member panel discussion of professionals engaged in developing AI tools and putting them into practice. The panel consists of representatives from Cisco, IBM and academia and the discussion is designed to address three related themes:

- How AI can foster inclusion in workplaces and society
- The challenges of biases and fairness in AI and strategies to overcome them
- What it takes to design truly inclusive AI systems

We summarize the panelists' main points including areas of agreement and disagreement in relation to each of these themes. We also attempt to shed light on how their own professional and personal contexts might be informing the views they share.

Next, drawing upon survey data we report on public perceptions regarding inclusion and its implications for AI. The survey themes we will report on are perceptions of AI fairness & bias; trust & transparency in AI; Accessibility & representation in AI; AI regulation & policy. We will also describe how responses are impacted by demographic considerations of respondents such as age, gender, ethnicity, education level and familiarity with AI tools.

The paper will highlight areas of convergence and divergence across related academic literature, the professional perspectives of the panelists and the public as represented by survey respondents. We then discuss the implications of our findings for AI development and dissemination. We further examine how our findings can inform communication and education related to AI and inclusion. This includes offering guidance to organizations and others about how to address user inclusion concerns on the one hand and on the other hand, how our findings can contribute to advancing AI's positive impact on inclusion.

References

Cachat-Rosset, G. & Klarsfeldb, A (2023). Diversity, equity, and inclusion in artificial intelligence: An evaluation of guidelines. *Applied Artificial Intelligence* 37(1) <https://doi.org/10.1080/08839514.2023.2176618>.

D'Agostino, S. (2023). How AI Tools Both Help and Hinder Equity. *Inside Higher Ed* (June 5.) <https://www.insidehighered.com/news/tech-innovation/artificial-intelligence/2023/06/05/how-ai-tools-both-help-and-hinder-equity>.

Eden, C.A., Onyebuchi, N.C. Adenyl, I.S. (2024). Integrating AI in education: Opportunities, challenges, and ethical considerations. *Magna Scientia Advanced Research and Reviews* 10(02), -6–13. <https://doi.org/10.30574/msarr.2024.10.2.0039>.

Ozili, P. K. (2021). Big data and artificial intelligence for financial inclusion: benefits and issues.

Miner, A. S., Milstein, A., & Hancock, J. T. (2017). Talking to machines about personal mental health problems. *Journal of the American Medical Association*. (October 3). *JAMA*. 2017;318(13):1217-1218.

Petracek, L. (2024). AI chatbots for mental health: Opportunities and limitations Can AI chatbots truly provide empathetic and secure mental health support?

Psychology Today July 17. <https://www.psychologytoday.com/us/blog/the-psyche-pulse/202407/ai-chatbots-for-mental-health-opportunities-and-limitations>.

West, S. M., Whittaker, M, & Crawford, K. (2019). Discriminating systems: Gender, race and power in AI. AI Now Institute.

World Health Organization (2021). Mental health workforce gap. <https://www.who.int/news/item/08-10-2021-who-report-highlights-global-shortfall-in-investment-in-mental-health>.

ORGANIZATIONAL COMPASSION IN THE DIGITAL ERA: A SYSTEMATIC LITERATURE REVIEW

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Keywords: Organizational compassion, well-being, digitization, employee outcomes.

The COVID-19 pandemic triggered the acceleration of the increased and expedited digitization of the work. The fast pace of this transition has affected various organizational factors, such as: employment conditions and relations (e.g., contract type, working hours, work location), work relations (e.g., quality of social interactions within the work environment), job content (e.g., task autonomy, task complexity and required skills) and leadership and organizational culture (Bednorz et al, 2022). Telework and ICT-mobile work have been reported to impact employee mental and physical health and wellbeing both positive and negatively. On the positive side, telework can improve work-life balance, help employees juggle child-care, improve autonomy regarding working time, increase motivation and productivity, and reduce absenteeism and turnover (Bodner et al, 2022; Gajendran, and Harrison, 2007). On the negative side, telework and digital management tools have also been associated with longer working hours, work-home interference, work intensification, social isolation and poor relationships with colleagues and supervisors (El Kadri Filho and Lucca, 2022; Mann and Holdsworth, 2003), making management tasks and supporting employees more difficult (Sardeshmuskh et al, 2012).

In addition, the pandemic has propelled the realization that End-of-Life (EoL) experiences (grief, loss, serious illness, etc.) are universal experiences that affect us all and that the working population is not spared from them. Europe's population with serious illnesses and palliative care needs is expected to continue to grow, affecting the active working population either as patients, caregivers or bereaved persons (Wilson et al, 2021). During their daily lives, people suffer the death of loved ones, the illness of oneself or a loved one, and grief (Rynes, Barunek, Dutton, and Margolis, 2012). Although such suffering and grief may not be desired within contemporary organizations (Peticca-Harris, 2019) as they are often viewed as "too heavy for the rarefied emotional atmosphere of the workplace" (Bento, 1994, p. 35), pain and suffering inevitably spills over from employees' personal lives to the workplace (Paakkanen, Martela, Hakanen, Uusitalo, and Pessi, 2021). This inevitable pain generated within organizations has become an important, yet difficult, challenge within organizations. Digitization and hybrid work can facilitate caregiving and working remotely while sick but it may also impede contact with colleagues and social support from peers which may lead to social isolation and lower organizational commitment.

The development of a more compassionate work culture, which emphasizes the human behind the employee and helps employees to cope with these new challenges, is needed. When suffering within the workplace is met with care and concern, compassion occurs (Peticca-Harris, 2019), making compassion in high demand in today's workplaces (Paakkanen et al., 2021). Compassion is defined as an interper-

sonal process involving the noticing, feeling, acting and sense-making that alleviate the suffering of another person (Dutton, Workman, and Hardin, 2014).

The surge of interest in compassion at work, catalyzed by Frost's (1999) assertion that compassion counts and that the inevitable pain existing within organizations requires an academic response, has resulted in a growing number of studies exploring the role of compassion in organizations, as well as scholarly work into its outcomes ((Guinot, Miralles, Rodríguez-Sánchez, and Chiva, 2020). Although the study of care and compassion goes back thousands of years (Rynes et al., 2012), primarily as an inevitable response to suffering within the dyadic relationship between a single sufferer and a focal actor (Kanov, Powley, and Walshe, 2017), only recently has it also been proposed as a collective capacity, and a dynamic social process (Lilius et al., 2011) in which employees collectively notice the suffering, feel and express their empathy and concern, and act to alleviate the suffering in a collective way (Lilius et al., 2011).

Following this paradigm, in the last few years an emergent body of research has suggested that organizational compassion can facilitate positive outcomes in organizations. For example, episodes of compassion at work have been associated with improved cooperation and trust, increased employee engagement and commitment, more prosocial behaviors, and lower turnover rates, absenteeism, and emotional exhaustion, and job-related burnout.

Despite the scholarly contributions of existing research, there is still an evident dearth in research on the topic which limits its further development and application and calls for more extensive empirical research on the organizational consequences of compassion as a collective capability, at the individual as well as at the organizational level, as empirical connections to compassion and organizational outcomes have been historically challenging to identify (Lilius et al., 2011).

In order to develop a reliable research agenda, it is paramount to know what has been investigated and the resulting findings of those studies. Therefore, this study attempts to provide answers to the following research questions:

Research Question 1: How organizational compassion has been conceptualized in the literature so far?

Research Question 2: What employee outcomes have been found as being significantly impacted by organizational compassion, and in what way?

To answer these questions, in the present research, we performed a systematic literature review (SLR). The SLR follows a replicable, scientific, and transparent methodology (Tranfield, Denyer and Smart, 2003). Compared to traditional narrative reviews, the SLR offers several advantages: i) enhanced quality of the review process and outcomes (Danese, Manfe, and Romano, 2018; Leonidou, Christofi, Vrontis, and Thrassou, 2018); ii) reduction of bias and errors (Dada, 2018); iii) increased validity due to the replicability of the steps applied during the review process (Wang and Chugh, 2014); iv) provision of literature mapping for a specific research area and data synthesis (Kauppi, Salmi, and You, 2018; Witell, Snyder, Gustafsson, Fombelle, and Kristensson, 2016); and v) a framework that integrates existing knowledge for researchers and practitioners (e.g., Dada, 2018; Nofal, Nicolaou, Symeonidou, and Shane, 2018). Our methodology consists of two research steps: the first involves identifying, reading, and understanding significant docu-

ments; and the second involves a content analysis of the identified articles.

In the first step, we started with the selection of the databases. The selection process concluded with the selection of the Pro-quest database, as it offers access to a vast array of academic journals, it provides sophisticated search tools that allow users to perform precise and efficient searches, including the use of controlled vocabulary and thesaurus terms, and includes peer-reviewed and high-impact publications, ensuring that the literature reviewed is of high quality and credibility. To avoid missing important and relevant references from our search, we also complemented the search in pro-quest with a manual search on Google Scholar through the monitoring of citations of further relevant articles in high-ranking quality journals. Although our major focus was on workplace compassion, we included also several relevant constructs to understand the full breadth of the construct. Specifically in our search we used the following primary keywords: compassionate workplaces, workplace compassion, organizational compassion, compassion in the workplace, compassionate leadership, compassionate management, compassionate climate, compassionate culture. We then combined each of these keywords with the following secondary keywords: employee well-being, employee engagement, employee productivity, job satisfaction, work absenteeism, employee stress levels, employee retention – turnover. We applied four major inclusion criteria for the selection of the articles that would be included in the systematic literature review. The first criterion concerned the inclusion of only peer-reviewed articles that were written in English. To avoid excluding any important and relevant articles, we did not specify a time period for our research. Second, we selected only articles published in peer-reviewed journals because they provide validated and rigorous scientific knowledge and are likely to have the highest impact in the field. Third, in line with our focus on organizational and business research, we focused our search on journals in the broad area of business, management and organizational studies. Fourth, we excluded all articles that did not at least partially define the concept of workplace compassion (or similar constructs) because they did not fit our main research aim of construct definition. In the next step, we reviewed the reference lists of these full texts to identify additional references that were omitted due to our initial search criteria but were still important for the definition of perceived organizational purpose. Overall, this search yielded 31 journal articles.

The second step consists of analyzing all the selected articles to identify emerging themes, by conducting a coding process using the Nvivo software. During the coding process, we will focus on two issues. First, in each source we will seek to identify different conceptualizations of organizational compassion. Second, we will seek to identify employee-level outcomes of workplace compassion. The results of this analysis will be presented during the Conference.

References

Bednorz, J., Sadauskaite, A., Czarzasty, J., and Surdykowska, B. (2022). Unionisation and the twin transition. Good practices in collective action and employee involvement. Study for the Policy Department for Economic, Scientific and Quality of Life Policies Directorate-General for Internal Policies, PE.

Bento, R. F. (1994). When the show must go on: Disenfranchised grief in orga-

nizations. *Journal of Managerial Psychology*, 9(6), 35-44.

Bodner, A., Ruhl, L., Barr, E., Shridhar, A., Skakoon-Sparling, S., and Card, K. G. (2022). The impact of working from home on mental health: a cross-sectional study of Canadian worker's mental health during the third wave of the covid-19 pandemic. *International Journal of Environmental Research and Public Health*, 19(18), 11588.

Dada, O. (2018). A model of entrepreneurial autonomy in franchised outlets: A systematic review of the empirical evidence. *International Journal of Management Reviews*, 20(2), 206-226.

Danese, P., Manfè, V., and Romano, P. (2018). A systematic literature review on recent lean research: state-of-the-art and future directions. *International Journal of Management Reviews*, 20(2), 579-605. Dutton, J. E., Workman, K. M., and Hardin, A. E. (2014). Compassion at Work. *Annual Review of Organizational Psychology and Organizational Behavior*, 1(1), 277-304.

El Kadri Filho, F., and de Lucca, S. R. (2022). Telework conditions, ergonomic and psychosocial risks, and musculoskeletal problems in the COVID-19 pandemic. *Journal of Occupational and Environmental Medicine*, 64(12), e811-e817.

Frost, P. J. (1999). Why compassion counts!. *Journal of Management Inquiry*, 8(2), 127-133.

Gajendran, R. S., and Harrison, D. A. (2007). The good, the bad, and the unknown about telecommuting: meta-analysis of psychological mediators and individual consequences. *Journal of applied psychology*, 92(6), 1524.

Guinot, J., Miralles, S., Rodríguez-Sánchez, A., and Chiva, R. (2020). Do compassionate firms outperform? The role of organizational learning. *Employee Relations: The International Journal*, 42(3), 717-734

Kanov, J., Powley, E. H., and Walshe, N. D. (2017). Is it ok to care? How compassion falters and is courageously accomplished in the midst of uncertainty. *Human Relations*, 70(6), 751-777.

Kauppi, K., Salmi, A., and You, W. (2018). Sourcing from Africa: a systematic review and a research agenda. *International Journal of Management Reviews*, 20(2), 627-650. Leonidou, Christofi, Vrontis, and Thrassou, 2018

Lilius, J. M., Worline, M. C., Dutton, J. E., Kanov, J. M., and Maitlis, S. (2011). Understanding compassion capability. *Human relations*, 64(7), 873-899.

Mann, S., and Holdsworth, L. (2003). The psychological impact of teleworking: stress, emotions and health. *New technology, work and employment*, 18(3), 196-211.

Nofal, A. M., Nicolaou, N., Symeonidou, N., and Shane, S. (2018). Biology and management: A review, critique, and research agenda. *Journal of Management*, 44(1), 7-31. Paakkanen, M., Martela, F., Hakanen, J., Uusitalo, L., and Pessi, A. (2021). Awakening compassion in managers—A new emotional skills intervention to improve managerial compassion. *Journal of Business and Psychology*, 36(6), 1095-1108.

Peticca-Harris, A. (2019). Managing compassionately? Managerial narratives about grief and compassion. *Human Relations*, 72(3), 588-612.

Rynes, S. L., Bartunek, J. M., Dutton, J. E., and Margolis, J. D. (2012). Care and compassion through an organizational lens: Opening up new possibilities. *Academy of Management review*, 37(4), 503-523.

Sardeshmukh, S. R., Sharma, D., and Golden, T. D. (2012). Impact of telework on exhaustion and job engagement: A job demands and job resources model. *New Technology, Work and Employment*, 27(3), 193-207.

Tranfield, D., Denyer, D., and Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British journal of management*, 14(3), 207-222.

Wang, C. L., and Chugh, H. (2014). Entrepreneurial learning: Past research and future challenges. *International journal of management reviews*, 16(1), 24-61.

Wilson, D. M., Punjani, S., Song, Q., and Low, G. (2021). A study to understand the impact of bereavement grief on the workplace. *OMEGA-Journal of Death and Dying*, 83(2), 187-197.

Witell, L., Snyder, H., Gustafsson, A., Fombelle, P., and Kristensson, P. (2016). Defining service innovation: A review and synthesis. *Journal of Business Research*, 69(8), 2863-2872.

Session B2

AI IN SOCIETY

**Chair: Ioannis Ntzoufras, Athens University of Economics and
Business, Greece**

DESIGNING ELIZABETH — AN AI RESEARCH TOOL FOR EMOTIONAL DEPTH, ADAPTIVE MEMORY, AND FIRST-ENCOUNTER “PRE-PERSONALIZATION”

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Keywords: AI companions, emotional intelligence, adaptive AI, elderly care, human-AI interaction, first-encounter pre-personalization.

Introduction

The global growth in aging populations, combined with the ongoing shortage of human caregivers, has triggered the development of AI companions — software that delivers functional assistance, emotional support, and above all empathetic companionship to lonely seniors. The most advanced commercial offerings, like ElliQ, Replika, and Xiaoice, have promised to address the shortage of human aides. Since they are commercial offerings rather than research tools, they offer little concrete data for assessing their performance, and even less data for researchers seeking to improve it.

We propose *Elizabeth* — a next-generation AI research platform that’s not only designed as a companion for seniors but also created specifically to advance the research in human-AI interaction, especially in the domain of care for the elderly. Elizabeth will need to exhibit empathetic behavior immediately, without reliance on the sort of massive data sets usually used to train chatbots. This is because every empathetic interaction is informed by experience with a specific individual; in contrast, writing a research report on a specific topic does not require a massive amount of insight into the individual making the request. Without some mechanism for providing Elizabeth with insight into the client before their first interaction, even the appearance of empathy is impossible, and the risk of social blunders is high.

Our guiding research questions are the following:

Q1: How can we design an empathetic companion, appropriate to a wide range of settings, from home care for the most alert clients, to assisted living for those most cognitively challenged?

Q2: How much specific differentiation will be required for Elizabeth, to enable the most effective client interactions?

Q3: How much specific personalization will be required for Elizabeth, to enable the most effective client interactions?

Q4: How much specific personalization will be required for Elizabeth, before the initial client interactions, to enable the most effective client interactions?

Q5: How can we measure Elizabeth’s contribution to the client’s sense of well-being?

Comparative analysis of existing AI companions

In order to put Elizabeth’s progress into context, we examine three leading commercially available AI companions — ElliQ, Replika, and Xiaoice — which each use a different model of AI-based interaction. The following comparison is based on their relative strengths and weaknesses, notably early-stage personalization.

The following table synthesizes their key attributes: While each of these systems

AI companion	Strengths	Limitations
ElliQ (Intuition Robotics)	Proactive reminders, health tracking, user-friendly design tailored for older adults	Limited emotional depth, relies on scripted responses that lack adaptability during early interactions
Replika (Luka Inc.)	Personalized dialogue via machine learning, adapts to user behavior over time	Early interactions feel repetitive and disconnected until enough user data accumulates
Xiaoice (Microsoft)	Advanced sentiment recognition, storytelling capabilities, social media integration	Heavily reliant on pre-scripted responses, limiting adaptability during first-time conversations

claims to succeeds in keeping users engaged once sufficient data has been gathered, they do not provide data to assess their performance or to determine in which settings they are most or least successful. They do not appear to have a mechanism for pre-personalization, that is, for creating good first impressions. Elizabeth is designed to address both shortcomings.

Limitations of current AI companions

Contemporary AI companions have four primary hurdles that limit their ability to establish and maintain genuine, emotionally nurturing relationships. This section includes an overview of existing Large Language Model (LLM) strategies deployed in these commercial implementations, evaluating where advancements could improve performance.

A. Emotional depth

Current systems apply sentiment analysis to determine surface-level emotional cues; they lack context-sensitive emotional reasoning capabilities. Turkle (2017) calls such simulated empathy shallow in nature. New LLMs such as GPT-4 and Google’s PaLM-2 now display emotion-aware dialogue generation — employing sentiment embeddings to track user mood during interactions. Zhang et al. (2024) studied emotion-conditioned language models capable of generating responses tailored to user emotional states and suggested a means for Elizabeth to simulate greater empathy. These alone will not address the limitations of an AI-companions first interactions.

B. Contextual memory

Among the main drawbacks of existing commercial AI companions is that they lack memory to recall past dialogue. Tschida et al. (2025) draws attention to how this leads to isolated, repetitive dialogue. The most recent literature on LLM memory architectures — Hatalis (2024), in particular — identifies episodic memory embeddings and long-context transformers that capture dialogue coherence over multiple sessions. Elizabeth uses these architectures so that she can store user preference, emotional cues, and past conversations — she can feel familiar and long-present

C. Personalization limitations

AI companions like Replika learn as time passes, but Zhang et al. (2024) believe that such learning is algorithmically constrained and dependent on predetermined personalization paths. Modern few-shot learning LLMs (like Meta’s LLaMA and Anthropic’s Claude) learn to generalize to new users with minimal input, rapidly fine-tuning conversational style to the user’s preference. Elizabeth employs such models, allowing her to generate personalized patterns of conversation from the first exchanges, reducing the need for large pre-training of conversational style. This is distinct from avoiding social blunders, described below.

D. First-Encounter social blunders

We expect that the most severe limitation of empathetic AI companions will involve early-stage social blunders. AI companions, lacking user data, fall back on default dialogue patterns that may be dramatically inappropriate. An early CRM system in a supermarket tried to lure back a customer to the fresh fish counter, unintentionally engaging the customer with in discussion of a recently deceased relative’s preferred menus. Lack of context concerning the individual client may result in extreme social blunders, like asking a client if she is seeing her daughter today, when the daughter is estranged, or seeing her husband, when the husband has just died. Elizabeth’s initial, and as yet primitive user classification system takes an insight from cluster-based persona modeling — an approach proposed by Huang et al. (2022) — which groups users according to communication inclinations and emotional profiles. A small pre-personalization tailoring session, conducted by a human aid, should allow Elizabeth to tailor her first-impression strategy appropriately.

Elizabeth: An AI research tool for empathetic engagement

Elizabeth’s evolution exceeds typical AI friendship paradigms in that it gives a response to a fundamental research question: How can an AI friend with no prior information conduct empathetic, personalized dialogue on initial meetings and avoid social missteps? To accomplish this, Elizabeth employs a multi-layered design that is based on two fundamental innovations: the preliminary briefing of the user and the tentative user categorization system.

1. Simple user preferences: This includes information like tone of conversations (e.g., formal, casual, or motivational), areas of interest (e.g., business news, fiction, etc.), and manner of interaction (e.g., serious discussions vs. light social talk).

2. Emotional factors: To avoid insensitive behavior, Elizabeth incorporates user-

specific emotional factors, like identified cognitive states or emotional sensitivities, according to affective computing research (Picard, 2003).

3. Contextual and cultural awareness: The briefing includes data regarding local dialects, cultural customs, and conditions of living in order for Elizabeth to properly modulate her mode of speaking and rate of communication — anticipating errors due to culture conflicts (Devjak et al., 2023).

A. Initial user briefing: Establishing a foundation for first encounters

This briefing, while short on detail, has Elizabeth approach the first conversation with a seasoned, adaptable benchmark — sidestepping the abrupt, across-the-board opening lines that too often lead to premature conversational collapse.

B. Tentative user classification: Guiding early personalization

Having in mind that a first-time user orientation would only provide an incomplete foundation, Elizabeth applies a temporary user categorization system to further restrict her conversational strategy. This system applies clustering models and persona modeling practices — based on Huang et al. (2022) — to assign a temporary user profile by similarity with previous user patterns.

The classification system operates in two stages:

1. Persona prediction:

Elizabeth compares the user’s first-time conversational behavior to pre-established clusters of personas depending on past interaction with other users. These language style embedding (Patel et al., 2023) clusters predict if a new user is like an “analytical conversationalist,” “emotional comfort-seeker,” “social storyteller,” or something else. This prediction directs the tone and content of the topics of conversation Elizabeth selects — for example, beginning with intellectual topics for an intellectual user or adopting a more gentle, comforting tone for a feeling comfort-seeker.

2. Adaptive recalibration:

Rather than relying on a static classification, Elizabeth constantly refreshes her user model throughout the conversation. Using the introduction of contextual embeddings — motivated by Hatalis (2024) — she is tracking shifting emotional cues, discourse rhythms, and user engagement trends. This supports real-time recalibration such that early misclassifications are minimized. If a user originally categorized as “analytical” responds with emotional openness, Elizabeth becomes adaptively adept at modifying dialogue style to an empathetic, supportive register.

C. Real-time conversation refinement: Closing the feedback loop

Other than the initial briefing and user classification, Elizabeth employs a real-time conversation tuning module to ensure flexibility in initial-stage conversations. The module continuously processes information related to conversation — i.e., semantic content, emotional tone, and latency of user response — and returns this information to the user model to tune the next dialogue. Elizabeth’s dialogue engine integrates principles from reinforcement learning with human feedback (RLHF) — a technique used in OpenAI’s ChatGPT (Ouyang et al., 2022) — to prioritize conversational pathways associated with higher user engagement and positive emotional signals. If the user displays signs of discomfort or disengagement (e.g., shorter responses, negative sentiment shifts), Elizabeth pivots, adjusting her tone and topic in real time to recover rapport.

This feedback loop ensures that even when initial assumptions prove to be erroneous, Elizabeth adapts quickly — preventing social gaffes and encouraging a freer, more empathetic conversational experience.

D. Ethical safeguards and user privacy

Attuned to the ethical ramifications of AI companionship — particularly for vulnerable populations, such as the elderly — Elizabeth’s design includes robust privacy-first ideals and ethical safeguards. Following the templates of Garg (2024), Elizabeth anonymizes user data in her initial briefing, with no traceable information remaining other than necessary personalization parameters.

Additionally, Elizabeth is built to disclose her AI nature at the beginning of the conversation, ensuring openness and setting realistic user expectations. To prevent emotional over-reliance, Elizabeth has conversation pacing mechanics — encouraging users to take breaks, pursue offline social contact, and maintain human relationships alongside her friendship.

Conclusion

Elizabeth is a new type of AI companionship — not merely as a functional tool for reminders and conversation, but as an exploratory platform for investigating how AI can emulate empathy and personalization from the start. By integrating an initial user briefing with temporary user classification, Elizabeth minimizes early social gaffes, promoting real emotional interaction from the start.

This research moves the field of human-AI interaction forward by addressing an understated challenge — ensuring AI companions start relationships off with empathy and personalization, even in the absence of existing data. Elizabeth thereby sets a higher standard for first-encounter personalization, redefining what it will mean for an AI companion to “get it right” — from the first moment.

References

- Devjak I, Kovač J, Trunk Širca N. 2023. Intercultural communication: Hampering and facilitating factors in international business. *J Intercult Manag* 15(2):21–44.
- Garg A. 2024. Ethical considerations in conversational AI: Addressing bias, privacy, and transparency. *Shodh Sagar J Artif Intell Mach Learn* 1(3):18–23.
- Hatalis K. 2024. Memory matters: The need to improve long-term memory in LLM-agents. *Proc AAAI Symp Ser*.
- Huang Q, Zhu X, Huang M. 2022. Personalized dialogue generation with persona-adaptive attention. *arXiv:2210.15088*.
- Ouyang L, Wu J, Jiang X, et al. 2022. Training language models to follow instructions with human feedback. *arXiv:2203.02155*.
- Patel A, Rao D, Kothary A, McKeown K, Callison-Burch C. 2023. Learning interpretable style embeddings via prompting LLMs. *Findings Assoc Comput Linguist EMNLP 2023*:15270–15290.
- Picard RW. 2003. Affective computing: Challenges. *Int J Hum Comput Stud* 59(1-2):55–64.
- Tschida J, Michael K, McDaniel T. 2025. Exploring social robots for healthy older adults: Aging with companionship. *IEEE Xplore*.
- Turkle S. 2017. *Reclaiming conversation: The power of talk in a digital age*.

Penguin Books.

Woodward K, Kanjo E, Brown DJ, McGinnity TM. 2020. On-device transfer learning for personalising psychological stress modelling using a convolutional neural network. arXiv:2004.01603.

Zhang Y, Yang X, Xu X, et al. 2024. Affective computing in the era of large language models: A survey from the NLP perspective. arXiv:2408.04638.

ALGORITHMS ARE LIKE SAUSAGES AND WE JUST CAN'T GET ENOUGH OF THEM: EXPLORING REGULATION AND PUBLIC AWARENESS FOR SOCIAL-MEDIA ALGORITHMS

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Keywords: Regulation, social-media, algorithmic-transparency, filter-bubbles, artificial-intelligence.

Introduction

Algorithmic engineering is too powerful to be left unchecked. AI-powered social media algorithms constitute a defining factor of our interface with reality. This paper argues for the urgent need of an active public discourse regarding algorithm-engineering (Cinelli et al., 2021). Public awareness in conjunction with relevant regulation may be appropriate to mitigate the potential adverse effects of unchecked application of AI algorithms (Dubois and Blank, 2018).

The increasing application of AI may result in users being served content overly aligned with their respective history of past choices and expressed preferences, exacerbating the “echo-chamber” effect (DiFranzo and Gloria-Garcia, 2017). This insulation from diversity deprives users of potential value in discovery and critical self-reflection (Barberá, 2015).

According to the aphorism “Laws are like sausages; it is best not to see them being made” (Widiss, 2015), the analogy highlights the opaqueness of production. In a democratic society, laws are made through transparent processes — algorithms should be no different. They embody value systems that can either exacerbate echo chambers or promote diversity (Mutz, 2006). This paper surveys major platforms via the literature to highlight this agenda and argues for the need for public awareness and regulation.

Social media algorithms and echo chambers

Facebook

Even though the expansion of the Internet made many people believe that it will contribute to the creation of a “collective intelligence”, the internet has assisted in the development of an “echo chamber” that fosters the spread of false information (Franziska, Katrin, Mechtild, & Wolfgang, 2019). For the spread of misinformation in the social media, “The Observer” underlines that we should not blame the fake news but rather the algorithms of the platforms (Holmes, 2016). So called bad algorithms are connected with filter bubbles as instead of providing the users with the full range of available information, they cause them to just obtain a specific part of propositions (Franziska et al., 2019). However, bad user behavior and/or biased users are related to “echo chambers” (Franziska et al., 2019), because the information about the behavior of user with similar interests or profiles creates patterns that can cause the echo chamber effect (Bruns, 2017). For instance, the bigger social media by users, Facebook, uses a pertinence ranking algorithm to sort the

posts. This algorithm examines three factors: affinity, weighting, and timeliness (Franziska et al., 2019). Affinity refers to the previous behavior of the user with the posts. Weighting includes parameters such as number of interactions with the post (like, share, comment) by the users and by the creator, and type of post (image, text, video). Timeliness represents how recent a post is. So, the more interaction a post has, the more interaction a user has with specific users, and the newer a post is, results to come first on the Facebook page. Nonetheless, in order to make the list more interesting, the algorithm includes some other factors. The criteria of the sorting are changed a little in order not to display again an already seen list of posts. Moreover, posts from people are ranked higher than posts from companies (Franziska et al., 2019). However, a negative effect of the ranking strategy of Facebook algorithm is that fosters preexisting users' behavioral patterns to create "filter bubbles" that leads to "echo chambers" where users' information behavior is crucial (Franziska et al., 2019). Filter bubbles exist and are created by the information of users' behavior but, importantly, nobody can keep the users as prisoners inside them (Davies, 2018).

Twitter - X

Because the details of the recommendation algorithms that social media are using are unknown, many researchers have used automated accounts to audit the algorithms (Duskin, Schafer, West, & Spiro, 2024). Many algorithmic audits have been made on Twitter now X. Chen, Pacheco, Yang, and Menczer (2021) argue that the initial friends' selection affects "the density, transitivity, and political homogeneity of an account's personal network" even though there is no persistent indication of ideological leanings in the news feed. According to Bandy and Diakopoulos (2021) Twitter's algorithmic timeline promotes external links and diversity of sources whereas possibly it expands the gap between party differences. On the other hand, Bartley, Abeliuk, Ferrara, and Lerman (2021) discovered that the algorithmic timeline on Twitter is increasing disparity in how friends' tweets are shown. Also, Duskin et al. (2024) concluded that Twitter algorithm for friends recommendation by itself do not create echo chambers as tends to recommend accounts with more ideological diversity and less political focus than users would select from their social environments.

YouTube

Many scholars have focused on studying the recommendation algorithm of YouTube, investigating their contribution in creating "rabbit holes". Rabbit holes can be considered as pathways that guide users toward progressively more extreme content. Brown et al. (2022) using automated accounts, detect that the recommendations of YouTube lead to political echo chambers and favor comparatively conservative content. Similarly, Hussein, Juneja, and Mitra (2020) and Papadamou et al. (2021) states that YouTube's algorithm creates filter bubbles and users by watching misinformative content leads to suggestions of similar content. Park and Park (2024) studied the filter bubble generated by AI recommendation system of YouTube and the echo chamber effect in divergence of political attitudes. The researchers used YouTube application programming interfaces (APIs) and Webometric Analyst 2.0 to collect lists of videos suggested by conservative and progressive news media, along with user responses. They found that almost 50% of the suggested by the YouTube

videos had similar content both with conservative news media and with progressive. This is an indication that AI algorithms create filter bubbles that narrow the ideological horizons of the users. However, Park and Park (2024) states that filter bubble for conservative news media was stronger than for progressive media. In other words, it is more likely to get similar ideological recommendations by the algorithm if you watch conservative media on YouTube. The authors also discovered that suggested videos from media with longer history (legacy media) was about one-third in the case of progressive channels, whilst one forth in the case of conservative. Proving that YouTube's AI algorithms aim to improve viewer awareness, loyalty, and engagement by fostering reliable news sources and reputable voices.

The way forward: public awareness and regulation

AI-powered algorithms are human-made artifacts. We create them and, in turn, they affect our access to information; we form them and they, in turn, form us. There is no neutral or natural state, nor any universal recipe for an algorithm. The parametrization is a conscious act with significant and far-ranging impact. The parameters may be such that they favour cross-cutting exposure or, conversely, they may foster homophily, echo-chambers and filter bubbles. This is a choice to be made by the relevant stakeholders: the platform proprietors, the respective regulating authorities, and, not least of all, the end-users. Herbert Lin (2019) offers fertile guidelines for truth-promoting algorithm construction. Complacency by the authorities -thus providing a carte blanche to the platforms and the operators- is not to the benefit of the users. Crucially, the users should have a say regarding the parametrization of algorithms.

There is evidence that shows that users are indifferent to the accuracy of the content and to the variety of viewpoints. Indeed, social media content is consumed as entertainment rather than information (Alan Dennis, 2019). This phenomenon could strengthen the basis for a public awareness campaign that would gradually educate users on the crucial impact of algorithms on their daily information diet. Operators, similarly, are, as anticipated, motivated by increasing user engagement that would drive up revenues. Truth may become irrelevant in the name of profits (Kara Swisher, 2020). Such practices may provide further basis for warranted regulation. Treating algorithms as de facto black boxes is justifiably objectionable. An important question to address is the extent to which algorithm-engineering should be partly regulated. In addition, public awareness achieved via a relevant campaign would strengthen the agency and the empowerment of end users.

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References

Bandy, J., & Diakopoulos, N. (2021). "More Accounts, Fewer Links: How Algorithmic Curation Impacts Media Exposure in Twitter Timelines." Proc. ACM

Hum.-Comput. Interact., 5(CSCW1): Ar-ticle 78.

Barberá, P., (2015). "Birds of the same feather tweet together: Bayesian ideal point estimation using Twitter data". *Political analysis*, 23(1), pp.76-91.

Bartley, N., Abeliuk, A., Ferrara, E., & Lerman, K. (2021). "Auditing Algorithmic Bias on Twitter," *Proceedings of the 13th ACM Web Science Conference 2021*: 65–73. Virtual Event, United Kingdom: Association for Computing Machinery.

Brown, M., Bisbee, J., Lai, A., Bonneau, R., Nagler, J., & Tucker, J. A. (2022). "Echo Chambers, Rabbit Holes, and Algorithmic Bias: How YouTube Recommends Content to Real Users." SSRN.

Bruns, A. (2017). "Echo chamber? What echo chamber? Reviewing the evidence," 6th Biennial Future of Journalism Conference (FOJ17). Cardiff.

Chen, W., Pacheco, D., Yang, K.-C., & Menczer, F. (2021). "Neutral bots probe political bias on social media." *Nature Communications*, 12(1): 5580.

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W. and Starnini, M., (2021). "The echo chamber effect on social media." *Proceedings of the National Academy of Sciences*, 118(9), p.e2023301118.

Davies, H. C. (2018). "Redefining Filter Bubbles as (Escapable) Socio-Technical Recursion." *Socio-logical Research Online*, 23(3): 637-654.

DiFranzo, D. and Gloria-Garcia, K., (2017). "Filter bubbles and fake news." *XRDS: crossroads, the ACM magazine for students*, 23(3), pp.32-35.

Dubois, E. and Blank, G., (2018). "The echo chamber is overstated: the moderating effect of political interest and diverse media". *Information, communication & society*, 21(5), pp.729-745.

Duskin, K., Schafer, J. S., West, J. D., & Spiro, E. S. (2024). "Echo Chambers in the Age of Algorithms: An Audit of Twitter's Friend Recommender System."

Franziska, Z., Katrin, S., Mechtild, S., & Wolfgang, G. S. (2019). "Fake News in Social Media: Bad Algorithms or Biased Users?" *JOURNAL OF INFORMATION SCIENCE THEORY AND PRACTICE*, 7(2): 40-53.

Holmes, R. (2016). "The problem isn't fake news, it's bad algorithms: Here's why", *Observer*.

Hussein, E., Juneja, P., & Mitra, T. (2020). "Measuring Misinformation in Video Search Platforms: An Audit Study" on YouTube.

Lin, H. (2019). The existential threat from cyber-enabled information warfare. *Bulletin of the Atomic Scientists*, 75(4), 187-196.

Makris, D., (2022). An investigation into innovation praxis: scaffoldings that support innovation generation in organisations (Doctoral dissertation, Athens University of Economics and Business, Management of Science and Technology Dept).

Makris, D.,(2022). "Meta-Intelligence: Forming the Scaffolding that Forms You". In *ISPIM Conference Proceedings* (pp. 1-11). The International Society for Professional Innovation Management (ISPIM).

Makris, D. and Soderquist, K.E., (2022). "Dynamic Repertoire: Actively Curating Scaffoldings To Boost Innovation Generation". In *ISPIM Conference Proceedings* (pp. 1-9). The International Society for Professional Innovation Management (ISPIM).

Moravec, P. L., Minas, R. K., & Dennis, A. R. (2019). Fake News on Social Media. *MIS quarterly*, 43(4), 1343-A13.

Mutz, D.C., (2006). Hearing the other side: Deliberative versus participatory democracy. Cambridge University.

Papadamou, K., Zannettou, S., Blackburn, J., De Cristofaro, E., Stringhini, G., & Sirivianos, M. (2021). "It is just a flu": Assessing the Effect of Watch History on YouTube's Pseudoscientific Video Recommendations.

Park, H., & Park, S. (2024). 'The filter bubble generated by artificial intelligence algorithms and the network dynamics of collective polarization on YouTube: the case of South Korea'. *Asian Journal of Communication*, 34: 1-18.

Swisher, K. (2020). Clean Up Your Act, Facebook, or We're Leaving. *International New York Times*, NA-NA.

Widiss, D.A., (2015). "Making sausage: what, why and how to teach about legislative process in a legislation or leg-reg course". *J. legal educ.*, 65, p.96.

THE SYSTEMIC FRAGILITY OF “ARTIFICIAL INTELLIGENCE”

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Keywords: Platform formation, competition, regulatory change, incumbent strategies, industry architecture.

Emerging Artificial Intelligence technologies appear astonishingly powerful.

But AI systems are also, famously, quite **fragile** – even “profoundly fragile.”¹ It seems AI can be easily disrupted, or damaged. The sources of AI’s *technical* fragility are extensive, and well-documented.

AI also is fragile in another sense. As an industry and a socio-technical force that is poised to remake large swaths of the economy, there are many higher-level vulnerabilities in the AI eco- system. This systemic fragility is less about the risk to AI, and more about how AI can create risks for the larger social and economic systems in which it operates.

The path of technological change: A simple historical model

Steam power in the 18th century; railroads in the 19th century; electrification, the internal combustion engine, and all things “digital” in the 20th; the emergence of the Internet, straddling the turn of the 21st century – every technological revolution has followed a similar trajectory in penetrating and shaping the economy, the culture and human society. The benefits —and the problems – develop and enter the public consciousness in three phases. The 1st Phase is all about the potential upside — emphasis on potential. Everything is future-oriented. Passionate evangelists, media excitement, a sense of hopeful disruption, grandiose predictions, and FOMO² O²-drunk investors — during this period it is hard to separate hype from reality, and hard to see where the true impact of the new technology will be felt. Then, the initial enthusiasm begins to cycle with darker interpretations, as pessimists weigh in. The stock market bubbles and bursts. Utopic and dystopic visions swirl together, inflaming the public imagination. But as disorienting as it may be – and every one of these revolutions was initially greeted with a mix of enthusiasm and alarm – the real payoffs, and the real risks, have not yet become apparent – because the technology is not yet in wide use.

Jumping then out of sequence to the 3rd **Phase**... we will see broad adoption of and accommodation to the new technologies. Over time – which may take decades – the economic consequences have become clear. Which jobs are created, which have been eliminated. Which business models will prosper and which may vanish altogether. Corporate incumbents are dethroned and new giants emerge. People adjust, learn how to drive a car, replace a fuse or recharge a battery, use a computer, book a flight, shop and read and communicate online, etc. The cultural changes emerge in the course of generations. In time, society is dominated by people who have grown up with these technologies and for whom the sense of excitement and

¹<https://cset.georgetown.edu/publication/ai-accidents-an-emerging-threat/>

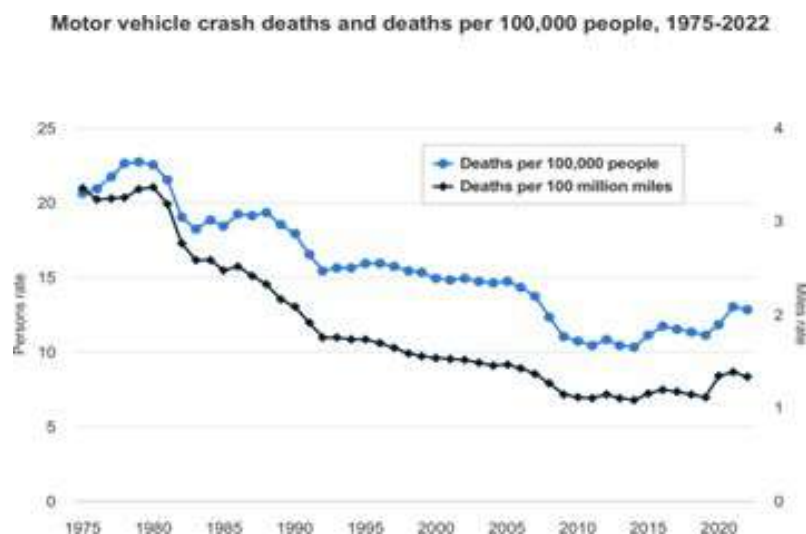
²FOMO = “Fear of Missing Out”

disruption has been replaced by a “new normal” — which isn’t even really “new” for them, since it is all they have ever known. And at this point things are “up and running” – the new technology is part of the economic infrastructure – and the benefits are clear and present, and the risks have been identified, regulated and managed.

The 2nd phase: The critical transition

In the middle of this multi-decade process of change and adaptation there is the turbulent 2nd Phase. As this case begins, the new technology comes out of beta test, and into the hands of ordinary people. It is real. It is achieving scale, and winning mass uptake – but the “guard-rails” have not yet been put in place. The new technology is in some sense out of control. It is creating new opportunities, of course, but new and often serious risks are becoming manifest as well.

Consider, for example, the emergence of the automobile as a mass consumer product, and how long it took before roads were fully adapted to accommodate high-speed mobility for multi- ton vehicles driven by regular people with limited education or experience, before there was safety glass, before seat belts or airbags, before emissions standards or mandatory child seats... The automobile was in reality a very dangerous innovation in its early days. In the 1930s, vehicular fatalities per 100 million miles traveled were 15 times higher than today³. It has only been in the last 10 years or so that by this measure the 2nd Phase of the automotive industry can be said to have concluded⁴.



A more recent example, just at the beginning of the 2nd phase, is cryptocurrency (a technology that is quasi-adjacent to artificial intelligence). Crypto has achieved “take-off” in the sense that it is now in use by millions of people, with annual transaction volumes in the tens of trillions of dollars, growing by 56% over the past year⁵. But with all that, it is still almost completely unregulated. The safety and supervisory measures that have been developed over the past century to regulate the

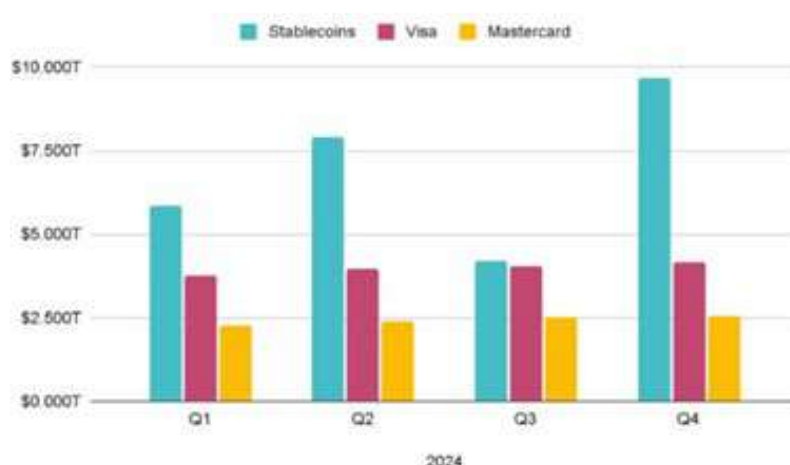
³https://en.wikipedia.org/wiki/Motor_vehicle_fatality_rate_in_U.S._by_year

⁴<https://www.ihs.org/topics/fatality-statistics/detail/yearly-snapshot>

⁵<https://www.trmlabs.com/post/report-teaser-proportion-of-illicit-volume-of-crypto-dropped-51-in-2024>

traditional financial industry are absent in the crypto world. Today, for example, the leading crypto platforms (stablecoins) operate at enormous scale – *\$27 trillion in total transaction volume* last year, far surpassing the global volume of Visa and Mastercard, without any requirement for audits or other financial disclosures⁶.

The consequences of allowing a wholly-unregulated industry to operate in this manner are painful and obvious, ranging from unstable technical platforms (with many spectacular collapses⁷), massive consumer losses, systemic financial risk and contagion, to fraud and outright theft (this past month the largest financial theft in dollar terms in human history took place in the cryptosphere⁸).



In short, it is in the 2nd phase that serious risks become apparent. In this phase, the market is real – it has taken off and is growing furiously. And yet the new technology is operating without safeguards or competent supervision. The positives outcomes are pulling the process forward.

But regulation is lagging, and technical countermeasures have not yet been fully developed.

In the 2nd phase, the technology is systemically fragile. It breaks a lot. It damages things. There are unexpected and unintended consequences. There are crashes and disasters. There may be criminality, or at least behavior that operates outside the law. People get hurt. There is the potential for social dislocation.

To put it in more academic terms, the 2nd phase is where what the economists call the “externalities” of the new technology become visible – the costs imposed on society which are not captured in the price of the technology itself, and not paid for by its producers or consumers.

Which bring us to AI.

The AI phase 2 scenario: How will it play out?

“Artificial Intelligence” is a label for a cluster of emergent technologies that seem to be coalescing into a new step-function change in the way information is processed

⁶<https://cryptoslate.com/stablecoins-surpass-visa-and-mastercard-with-27-6-trillion-transfer-volume-in-2024/>

⁷<https://www.nber.org/papers/w31160>

⁸<https://www.voanews.com/a/north-korea-behind-1-5-billion-crypto-theft-fbi-says/7989814.html>

and used. There is a broad consensus that its impact will be profound, though there is still considerable disagreement as to many details.

Viewed through the simplified lens of the technological change model articulated here, we can say that AI today has largely passed through the 1st Phase, and is on the threshold of the 2nd Phase. This means that — unlike the dystopic and science-fictionish predictions that abound in the 1st Phase (killer robots and the end of humanity and all that) — the real risks and the real downside of AI are starting to become visible. The externalities are beginning to be concretely calculable. In this paper, I will review the major areas of concern, the systems fragilities, for AI in the 2nd Phase — i.e., the larger risks that are starting to appear, and the externalities that AI is beginning to create which generate costs for society and potentially harmful economic impacts. Some of these vulnerabilities have been widely commented. Others are only now becoming visible. I will group them into five categories: technical, fundamental, eco-systemic, financial, and potential single-point failures.

Technical risks

These are risks arising from the way AI operates today, especially in the inference mode, which can produce potentially harmful results. These issues are fairly well known, although they are all still largely uncontrolled for. They include:

- Hallucinations
- Dangerous content
- Black Box problems (interpretability)
- Jailbreaking

Fundamental risks

These are risks arising from the methods used for training AI models, which threaten to limit or weaken its capabilities and potentially increase the risks for users:

- The looming shortage of training data
- Frictions in the training process (data quality, bias)
- The risks of synthetic data and model distillation
- Recursive Model collapse

AI Eco-system risks

These are risks arising from the needs that AI imposes on its eco-system, which create costs that society as a whole will have to bear — i.e., these are classic externalities:

- Power requirements
- Water requirements
- Pollution impact

Financial risks

These are risks arising from the distortions created by AI in the financial system:

- Private Sector Misallocation of Capital (Market Bubbles)
- Geopolitical Misallocation of Capital (Govt-driven Industrial Policies)
- Vulnerabilities in the Financial System due to AI malfunctions or “accidents”

Single-point failure nodes

AI seems to lead to an increased concentration of market power in certain key segments of the economy. In the most severe cases, this may create single-point failure risks in the form of chokepoints in supply chain.

Currently there are at least three potential chokepoints in the hardware supply chain for AI, identified with firms that are in effect monopolies for critical components of the AI eco-system:

- Nvidia (AI chips)
- TSMC (fabrication)
- ASML (semiconductor manufacturing equipment)

A problem at any of these chokepoints would at least temporarily cripple the AI industry.

Goal of the paper As the AI trend moves into the 2nd Phase, with mass adoption and multiplying applications in many fields, the risks will multiply as well. Taken together, this survey of the ways on which this powerful, but fragile trend will help define **a framework for policy-makers** to take into account in developing regulatory and technical “guard-rails” for the emergent AI-infused world. Where possible, **a quantitative assessment** of each of these risk categories will be provided, and a sense of the **prioritization** of countermeasures developed.

SYSTEMATIC FRAMEWORK FOR OPTIMUM UTILISATION OF LLM'S FOR SME MANAGERS

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Keywords: Artificial intelligence (AI), small and medium-sized enterprises (SMEs), prompt engineering optimisation, SME business challenges, LLMs.

Introduction

The digital age presents both opportunities and challenges for small and medium-sized enterprises (SMEs). The challenges of digital transformation are broad (Om-rani, Rejeb et al. 2022). With the swift development of AI, and in particular an increasing variety of large language models (LLMs), there are many opportunities for SMEs to grow their competitive advantage, streamline their operations, improve their decision-making, and foster innovation. LLMs are advanced AI systems that have provoked much media attention especially following the release of versions of ChatGPT (Mathieu, Anas et al. 2024). They are improving rapidly (Naveed, Khan et al. 2023). However SMEs face challenges in adopting AI due to a range of factors such as cost constraints, lack of technical expertise, and concerns about data privacy and security. The aim of this paper is to present a systematic framework that can assist SME managers in understanding, selecting and effectively utilising LLMs to overcome these challenges.

Methodology

This research presents a review of academic literature and industry reports to provide a synthesis of current knowledge regarding the landscape of AI adoption in SMEs: the fundamentals and capabilities of LLMs, as well as the limitations and the crucial role of prompt engineering. Drawing on this research, the paper presents a seven step framework that can guide SME decision-makers through the process of successfully optimising and implementing the use of LLMs within their businesses.

Key Findings

There is no doubt that AI offers transformative potentials for SMEs and LLMs are a revolutionary technology here (Bourdin, Paviot et al. 2024). However there are significant barriers to AI adoption in SMEs, the most common ones being costs and resource constraints, lack of AI knowledge and expertise, privacy and security concerns, organisational readiness and cultural resistance. A survey by Hadi, Qureshi et al. (2023) indicates that the challenges associated with using LLMs in real-world scenarios included ethical considerations, model bias, how to interpret the results, and computational resource requirements. SMEs often have limited budgets and may struggle to find the necessary resources. Data privacy concerns will necessarily arise once AI is implemented in a business. Incorporating AI solutions into existing legacy systems may be complex and time-consuming. SMEs may struggle to find and retain employees that have the necessary AI expertise (Huseyn, Ruiz-Gándara

et al. 2024). Many SME managers lack awareness of the potential benefits and how to implement LLMs effectively. In terms of organisational readiness, adopting AI requires a certain level of digital maturity, including changes to business processes and organisational culture: and some SMEs may be hesitant to embrace such significant transformations (Zhang 2024). There is also the issue of trust and acceptance level: employees may be resistant to AI adoption due to concerns about their own job security, as well as the privacy and reliability issues. Building trust and addressing these concerns will be crucial (McGrath, Cooper et al. 2024).

Prompt engineering is essential to maximising the value of LLMs. Clear, concise, and specific prompts are critical (Chen, Zhang et al. 2023). Advanced prompt engineering techniques such as chain of thought prompting, few shot learning, and role prompting can significantly enhance LLM performance. Without a good understanding of prompting techniques, SME managers will struggle to communicate effectively with the powerful systems available and will not get optimal value out of them. Basic guidelines include clear and specific prompts rather than ambiguous and vague prompts. Providing context can improve accuracy and relevance. Advanced prompt engineering techniques such as chain of thought prompting enables SMEs to leverage LLMs for complex problem-solving and decision-making. By instructing the model to think step-by-step or break down problems into smaller subtasks, SME managers can extract more sophisticated reasoning and analysis. Prompt engineering enables SME managers to customise outputs to suit their specific requirements. Techniques such as role prompting, whereby the model is instructed to assume a specific persona or expertise ensures that the generated content aligns with the desired perspective and knowledge base. Well crafted prompts streamline SME interaction with LLMs, reducing the time required to obtain the desired results. Prompt engineering requires experimentation and exploration. As noted by Sahoo, Singh et al. (2024), prompt engineering is an indispensable technique for getting the most out of LLMs and enhancing model efficacy.

Discussion/Implications

SME managers should create a culture that embraces AI. Government associations may have an important role to play in providing support and resources to support AI adoption in SMEs. AI implementation should be approached in a strategic fashion, starting with pilot projects and focusing on specific use cases that align with the SME's core business objectives. Issues to be considered include the readiness of the organisation, the current technological infrastructure, and existing practices in data management. Also needing to be considered is the way in which AI will be used. This will aid in producing a roadmap for introducing AI and particularly LLMs. Staff training and recruitment issues must be considered. A culture of innovation and continuous learning is necessary. As with any change program, defining KPIs in line with business objectives and monitoring these is important. Iterative improvement can then be implemented. In particular, managers need structured assistance in coming to grips with LLMs, their particular requirements and their fit with the business goals and with the manager's style. As noted by Bourdin, Paviot et al. (2024), managers of SMEs currently lack the know-how to use such technologies

and there is very little available in the literature to help them, and managers are struggling with this and need advice now.

Framework

The framework below provides a structured approach to understand, select and utilise LLMs through seven steps:

1. Play; encourage experimentation and exploration of various LLMs and other AI tools
2. Pain Point; identify the specific business problems or challenges that AI can address in your business
3. Prioritise the right model: a deeper understanding of the various LLMs and their capabilities, strengths and limitations
4. Polish your prompting: develop proficiency in prompt engineering techniques to optimise interactions with LLMs
5. Prepare your business data: ensure data is appropriately clean, formatted and organized for effective use with the chosen LLM
6. Personalise your use case: no one solution will suit everybody
7. Perform post mortem analysis: continuously evaluate the output of LLM usage and gather feedback from people in different roles

This framework has been derived from existing literature, with information combined in a sequence to optimise SMEs' competitive advantage. Each step builds upon the previous one. As noted by Szilágyi and Tóth (2023), managers have many factors to consider when choosing to introduce an LLM into their business. Differing SME contexts may present differing challenges in implementing this framework. While there are some existing methodologies, for example that of Hussain and Rizwan (2024), they lack the specific SME business context provided herein, or are more focused upon specific aspects such as cyber security (Jayathilaka and Wijayanayake 2025).

There are several strands within literature that can provide theoretical support for this model. For example, the dynamic capabilities framework of Teece (2023) is relevant in that SMEs need to develop capabilities to remain competitive and LLMs provide enormous advantage here. The initial step of "play", which suggests experimentation, is in line with this theory. The resource-based view (Ferreira and Ferreira 2024) suggests that firms can gain competitive advantage by leveraging their unique capabilities and resources, and once again LLMs are a potential resource, particularly relevant to the "prioritise" step. Further, the technology acceptance model (Davis and Granić 2024) explores how users come to accept new technologies and may provide some understanding regarding SME managers' adoption of LLMs. Diffusion of innovation theory explains how why and at what rate new ideas and technologies spread (Mbatha 2024). This justifies the need for a structured approach when LLMs are adopted in SMEs and is relevant particularly to the "prepare" step

above.

Conclusion

The effective use of LLMs represents a significant opportunity for SMEs to thrive in the digital age. Through understanding the nuances of these technologies, addressing the associated challenges, and using a structured approach such as the seven step framework presented herein, managers can harness the power of AI to achieve their business goals, foster innovation, and create a more sustainable future. Future research will focus on testing the seven step framework through interviews with managers of relevant SMEs.

References

- Bourdin, M., T. Paviot, R. Pellerin and S. Lamouri (2024). "NLP in SMEs for industry 4.0: opportunities and challenges." *Procedia Computer Science* 239: 396-403.
- Chen, B., Z. Zhang, N. Langrené and S. Zhu (2023). "Unleashing the potential of prompt engineering in Large Language Models: a comprehensive review." *arXiv preprint arXiv:2310.14735*.
- Davis, F. D. and A. Granić (2024). *Evolution of TAM. The technology acceptance model: 30 years of TAM*, Springer: 19-57.
- Ferreira, N. C. and J. J. Ferreira (2024). "The field of resource-based view research: mapping past, present and future trends." *Management Decision*.
- Hadi, M. U., R. Qureshi, A. Shah, M. Irfan, A. Zafar, M. B. Shaikh, N. Akhtar, J. Wu and S. Mirjalili (2023). "Large language models: a comprehensive survey of its applications, challenges, limitations, and future prospects." *Authorea Preprints*.
- Huseyn, M., Á. Ruiz-Gándara, L. González-Abril and I. Romero (2024). "Adoption of artificial intelligence in small and medium-sized enterprises in Spain: The role of competences and skills." *Amfiteatru Economic* 26(67): 848-866.
- Hussain, A. and R. Rizwan (2024). "Strategic AI adoption in SMEs: A Prescriptive Framework." *arXiv preprint arXiv:2408.11825*.
- Jayathilaka, H. and J. Wijayanayake (2025). "Systematic Literature Review on Developing an AI Framework for SME Cybersecurity Identification and Personalized Recommendations." *Journal of Desk Research Review and Analysis* 2(2).
- Mathieu, B., N. Anas, P. Thomas, P. Robert and L. Samir (2024). "Exploring the applications of natural language processing and language models for production, planning, and control activities of SMEs in industry 4.0: a systematic literature review." *Journal of Intelligent Manufacturing*: 1-21.
- Mbatha, B. (2024). *Diffusion of innovations: How adoption of new technology spreads in society. Information, Knowledge, and Technology for Teaching and Research in Africa: Human Machine Interaction and User Interfaces*, Springer: 1-18.
- McGrath, M. J., P. S. Cooper and A. Duenser (2024). "Users do not trust recommendations from a large language model more than AI-sourced snippets." *Frontiers in Computer Science* 6: 1456098.
- Naveed, H., A. U. Khan, S. Qiu, M. Saqib, S. Anwar, M. Usman, N. Akhtar, N. Barnes and A. Mian (2023). "A comprehensive overview of large language models." *arXiv preprint arXiv:2307.06435*.

Omrani, N., N. Rejeb, A. Maalaoui, M. Dabić and S. Kraus (2022). "Drivers of digital transformation in SMEs." IEEE transactions on engineering management.

Sahoo, P., A. K. Singh, S. Saha, V. Jain, S. Mondal and A. Chadha (2024). "A systematic survey of prompt engineering in large language models: Techniques and applications." arXiv preprint arXiv:2402.07927.

Szilágyi, R. and M. Tóth (2023). "Use of LLM for SMEs, opportunities and challenges." Journal of Agricultural Informatics 14(2).

Teece, D. J. (2023). "The evolution of the dynamic capabilities framework." Artificiality and sustainability in entrepreneurship 113: 238.

Zhang, H. (2024). "Leveraging AI for small and medium-sized enterprises (SMEs): exploring real-world applications of AI in business."

Session C2

**STRATEGY, TRANSFORMATION
AND DIGITAL RESILIENCE**

Chair: Josep Tribo, Stevens Institute of Technology, USA

QUO VADIS DIGITAL STRATEGY? A FRAMEWORK AND LOGIC FOR DIGITAL STRATEGY

Kalle Lyytinen

Case Western Reserve University

Keywords: Digital strategy, service stacks, digital logic.

As a sign of the rise of the digital (era) many claim that digital strategy is now the business strategy. However, the literature on the digital-strategy nexus lacks a precise, operational definition of digital strategy. Scholars and practitioners need frameworks to conceptualize digital strategy in ways that capture the new realities of today's pervasive digital environment.

This paper addresses the gap by proposing a first-principled definition, a theoretical framework and its operationalization. We adopt the core guidance view of strategy and define digital strategy as the smallest set of choices that, subordinate to the primacy of digital objects, optimally guide (or force) other firm level choices. The definition emphasizes how, in contemporary business strategy, it is digital objects that underpin most novel (digital) value propositions. These value propositions necessitate simultaneous alignment of the service stack in three generative relationships – operational, virtual, and contextual embeddings – that map digital objects to both material and social (business) worlds. Digital objects and their arrangements into service stacks, therefore, assume a central role in shaping the firm's strategic choices. We advance a theoretical framework that connects the unique constructs of digital strategy, service stacks, embeddings and related digital logic, to strategic choices covering three firm-level activities: digital visioning, service stack architecting, and leverage point recognition and manipulation. These three interdependent, cyclical, and recursive activities result in coherent strategic choices guiding the firm's search for value creation and capture opportunities unlocked by digital logic. We clarify the theoretical and practical relevance of the proposed framework by probing a representative sample of recent strategic decisions enacted by legacy automakers as they confront the ongoing digital disruption of their industry. We conclude by introducing open research questions for scholars and implications for practice.

DIGITAL TRANSFORMATION AND ENTERPRISE RESILIENCE MANAGEMENT IN CHINA

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Keywords: Digital transformation, resilience, absorptive capacity, commitment of stakeholders.

Introduction

In this paper, we study the relationship between digitalization-based strategic transformation and resilience. Some scholars have emphasized the positive role of enterprise digitalization in resilience, such as enhancing competitiveness and organizational adaptability through digital improvements (Caputo et al., 2021; He et al., 2023; Khurana, Dutta, & Ghura, 2022). However, other scholars have questioned the effectiveness of digital transformation. Salovaara, Lyytinen, and Penttinen (2019) pointed out that digital organizations still face reliability challenges in operational management. The management capabilities of enterprises lag behind the transformation of digital technologies, or the integration of digital technologies with existing resources is difficult, resulting in insignificant performance growth after digitization (Sia, Weill, & Zhang, 2021; Usai et al., 2021).

The aforementioned debates in the literature indicate that there is no consensus on the impact of enterprise digital transformation on resilience. Besides, one of the challenges in elucidating the relationship between digital transformation and corporate resilience lies in identifying the underlying mechanisms connecting both variables.

Our study, which relies on panel data of 2,327 listed companies on the China A-share market from 2011 to 2020, finds that digital transformation indeed contributes to enhancing enterprise resilience. In this relationship, we investigate the mediating role played by absorptive capacity and stakeholders' commitment as a mechanism connecting both variables.

Theory and hypotheses

Enterprise digital transformation and enterprise resilience

Digital transformation for enterprises is not only the application of digital technologies but also a process of organizational change (Matt, Hess, & Benlian, 2015). Enterprise resilience is a situational concept derived from adversity, referring to the ability of enterprises to respond to adverse environmental shocks (Williams et al., 2017). Also, resilience is connected to the ability of enterprises to bounce back when facing crisis as well as the ability to learn and improve after setbacks (Linnenluecke, 2017).

We rely on the theory of enterprise survival management to explain the relationship between digital transformation and enterprise resilience. Dynamic capabilities are the foundation of enterprise survival and the fundamental ability to adapt to complex and changing external environments (Salvato & Vassolo, 2018). Relevant

studies have shown that the application of digital technologies can strengthen and upgrade dynamic capabilities, helping enterprises adjust their business models in a timely manner and achieve adaptive evolution (Warner & Waeger, 2019; Ye et al., 2023). Therefore, the construction of digitally-driven dynamic capabilities may have a positive effect on enhancing enterprise resilience. In addition, the resource-based view is an important theoretical support for studying enterprise survival. Its assumption is that unique resources and capabilities are the source of sustained competition (Makadok & Barney, 2001). Bardoel and Drago (2021) argue that resilient capabilities are generated through structural resources, cognitive resources, relational resources, and other resources, which enterprises must cultivate to enhance resilience. Through continuous digital transformation, enterprises strengthen the repetitive and combinatorial utilization of various internal and external resources, internalize their own experiences into organizational resilience genes, and accumulate unique digital resources, which can help promote resilient growth (Han & Trimi, 2022). Hence, our first hypothesis reads as follows:

Hypothesis (H1): Digital transformation has a positive impact on enterprise resilience.

The role of absorptive capacity in shaping enterprise resilience through digital transformation

Absorptive capacity refers to the ability of an enterprise to identify, evaluate, and apply internal and external resources from the external environment (Cohen & Levinthal, 1990; Yao & Chang, 2017). Literature views absorptive capacity as a multidimensional construct, including the dimensions of knowledge identification, acquisition, conversion, and application (Cohen & Levinthal, 1990; Fosfuri & Tribo, 2008). We argue that digital transformation positively promotes absorptive capacity and thereby contributes to enterprise resilience management.

On the one hand, digital transformation can enhance the ability of enterprises to identify and acquire internal and external knowledge or information, which is crucial for improving their ability to respond to crises. At the same time, the diversification of the knowledge stock also provides enterprises with richer potential to improve strategic flexibility and identify external opportunities and threats (Fleming & Sorenson, 2001). On the other hand, digital transformation also promotes the ability of enterprises to transform and utilize information or knowledge. Based on the construction of underlying digital technologies and the practical application of technology, enterprises can change their value propositions and business logic, which creates great potential for resilience (Zhu et al., 2006). In other words, through digitization, enterprises enhance their ability to analyze, predict, and intervene in products, restructure and adjust strategic focuses and directions, and optimize strategic decision-making, which helps improve their understanding and adaptability to environmental changes. Hence, improvement of absorptive capacity through digitalization has a positive impact on enterprise resilience. Therefore, our second hypothesis is as follows:

Hypothesis (H2): Enterprise absorptive capacity mediates the relationship be-

tween digital transformation and corporate resilience.

The role of stakeholder's commitment in shaping resilience through digital transformation

From the perspective of inter-organizational relationships, stakeholder commitment promises to enhance the resilience of businesses through resource sharing and value co-creation in the digital ecosystem (Barney, 2018). Siachou, Vrontis, and Trichina (2021) found that establishing strong relationships with partners can better coordinate external resources and facilitate business operations, which is also a key source of enhancing organizational resilience. Furthermore, digital empowerment breaks the boundaries of traditional factors, providing opportunities for value co-creation among stakeholders (Jacobides, Cennamo, & Gawer, 2018; Tamym et al., 2021). The exchange of data between businesses and stakeholders accumulates data capital, leading to "learning by doing" based on real-world data. This collaborative value creation promotes strong relationships between companies and their stakeholders (Matarazzo et al., 2021). In times of crisis, stakeholders commit to playing the role of "trust insurance," as trust-based support is more likely to help businesses navigate crises and promote their resilience in the face of external shocks. Based on this argument, we can claim that:

Hypothesis (H3): Enterprise stakeholder commitment mediates the relationship between digital transformation and corporate resilience.

Data

Database

We conduct empirical analyses using data from Chinese companies. We take the listed companies on the A-share market in China from 2011 to 2020 as the initial research sample. The data in this article covers a total of 15365 observation samples of listed companies on the A-share market in China. Among them, the "Management Discussion and Analysis" (MD&A) text data of the listed companies comes from the China National Research Data Service (CNRDS), the enterprise financial data and market transaction data are mainly from the China Stock Market and Accounting Research (CSMAR), and the relevant data at the regional level is obtained from the China City Statistical Yearbook.

Variable settings

Resilience: In this paper, we use stock price volatility to measure corporate resilience

Digital transformation: We use textual analysis method to count the digital-related keyword frequency of annual reports as the proxy variable of digital transformation

Absorptive capacity: We adopt the percentage of digital intangible assets to total intangible assets.

Stakeholder commitment: We use the score provided by CSMAR on Supplier, Customers and other collaborators.

Control variables: firm size, financial leverage, company profits, growth rate,

management shareholding, managerial tenure, the average age of the board of directors, employee efficiency and the level of network development.

Results

Data shows that the linear coefficient of digital transformation on a fixed-effect estimation of organizational resilience is positive and passed the significance test at the 1% level. Therefore, hypothesis 1 of this study is supported. We also show the robustness of the results once we tackle endogeneity concerns using an instrumental variable approach and taking as an instrument the regional technological market turnover. We tested hypothesis 2, by adding the mediating variable (absorptive capacity-related variables) in the estimation. The results show a partial mediation result. Finally, to test hypothesis 3, we examined the mediating role of stakeholder commitment between digital transformation and resilience management in enterprises. The results found are that stakeholder commitment of enterprises plays a partially mediating role.

Conclusions

Our research findings show that digital transformation can promote resilient management in enterprises. We also emphasize the partially mediating role of absorptive capacity and stakeholder commitment in explaining the relationship between digital transformation and enterprise resilience.

The results found allow extracting the following managerial recommendations. First, enterprises must build a digital transformation plan that aligns with their own goals and characteristics and improve a firm's absorptive capacity through digital skills training and accurate use of digital technologies. Such a combination of elements will make organizations more resilient. Second, as digital resources become new production factors, strategic managers should promote commitment relationships between different types of stakeholders as a way to facilitate the connection between digitalization and enterprise resilience. Through this process, organizations will be more prepared to adapt and even to lever on different types of shocks to generate value.

Finally, we have conducted some preliminary analysis on the robustness of our results in situations of financial distress and the results hold. To investigate this issue in different institutional contexts (outside China) will be the subject of future research.

References

- Abrell T., Pihlajamaa M., Kanto L., vom Brocke J., & Uebernickel F. (2016). The role of users and customers in digital innovation: Insights from B2B manufacturing firms. *Information & Management* 53(3), 324-335.
- Aghion P., Bloom N., Blundell R., Griffith R., & Howitt P. (2005). Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics* 120(2), 701-728.
- Aghion P., Van Reenen J., & Zingales L. (2013). Innovation and Institutional Ownership. *American Economic Review* 103(1), 277-304.
- Albuquerque R., Koskinen Y., Yang S., & Zhang C. (2020). Resiliency of envi-

ronmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies* 9(3), 593-621.

Allenby B., & Fink J. (2005). Toward inherently secure and resilient societies. *Science* 309(5737), 1034-1036.

AlNuaimi B. K., Singh S. K., Ren S., Budhwar P., & Vorobyev D. (2022). Mastering digital transformation: The nexus between leadership, agility, and digital strategy. *Journal of Business Research* 145, 636-648.

Amit R., & Han X. (2017). Value Creation through Novel Resource Configurations in a Digitally Enabled World. *Strategic Entrepreneurship Journal* 11(3), 228-242.

Banalieva E. R., & Dhanaraj C. (2019). Internalization theory for the digital economy. *Journal of International Business Studies* 50(8), 1372-1387.

Barcos L., Barroso A., Surroca J., & Tribo J. A. (2013). Corporate social responsibility and inventory policy. *International Journal of Production Economics* 143(2), 580-588.

Bardoel E. A., & Drago R. (2021). Acceptance and Strategic Resilience: An Application of Conservation of Resources Theory. *Group & Organization Management* 46(4), 657-691.

Barney J. B. (2018). Why resource-based theory's model of profit appropriation must incorporate a stakeholder perspective. *Strategic Management Journal* 39(13), 3305-3325.

Bode C., Wagner S. M., Petersen K. J., & Ellram L. M. (2011). Understanding responses to supply chain disruptions: Insights from information processing and resource dependence perspectives. *Academy of Management Journal* 54(4), 833-856.

Boynton A. C., Zmud R. W., & Jacobs G. C. (1994). The influence of IT management practice on IT use in large organizations. *MIS quarterly* 299-318.

Brynjolfsson E., & McElheran K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review* 106(5), 133-139.

Buyl T., Boone C., & Wade J. B. (2019). CEO Narcissism, Risk-Taking, and Resilience: An Empirical Analysis in US Commercial Banks. *Journal of Management* 45(4), 1372-1400.

Caputo A., Pizzi S., Pellegrini M. M., & Dabić M. (2021). Digitalization and business models: Where are we going? A science map of the field. *Journal of Business Research* 123, 489-501.

Chang C.-H., Chen S.-S., Chen Y.-S., & Peng S.-C. (2019). Commitment to build trust by socially responsible firms: Evidence from cash holdings. *Journal of Corporate Finance* 56, 364-387.

Chen W., Zhang L., Jiang P., Meng F., & Sun Q. (2022). Can digital transformation improve the information environment of the capital market? Evidence from the analysts' prediction behaviour. *Accounting and Finance* 62(2), 2543-2578.

Chen Y., & Xu J. (2023). Digital transformation and firm cost stickiness: Evidence from China. *Finance Research Letters* 52, 103510.

Codara L., & Sgobbi F. (2023). Resilience, complexity and digital transformation: three case studies in the valves industry. *Journal of Manufacturing Technology Management* 34(9), 1-19.

Cohen W. M., & Levinthal D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly* 128-152.

Conz E., & Magnani G. (2020). A dynamic perspective on the resilience of firms: A systematic literature review and a framework for future research. *European Management Journal* 38(3), 400-412.

Durnev A., Morck R., Yeung B., & Zarowin P. (2003). Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research* 41(5), 797-836.

Dushnitsky G., & Lenox M. J. (2005). When do incumbents learn from entrepreneurial ventures?: Corporate venture capital and investing firm innovation rates. *Research Policy* 34(5), 615-639.

Escribano A., Fosfuri A., & Tribo J. A. (2009). Managing external knowledge flows: The moderating role of absorptive capacity. *Research Policy* 38(1), 96-105.

Farah B., Chakravarty D., Dau L., & Beamish P. W. (2022). Multinational enterprise parent-subsidiary governance and survival. *Journal of World Business* 57(2).

Faruquee M., Paulraj A., & Irawan C. A. (2021). Strategic supplier relationships and supply chain resilience: Is digital transformation that precludes trust beneficial? *International Journal of Operations & Production Management* 41(7), 1192-1219.

Fee C. E., Hadlock C. J., & Pierce J. R. (2009). Investment, financing constraints, and internal capital markets: Evidence from the advertising expenditures of multinational firms. *The Review of Financial Studies* 22(6), 2361-2392.

Fiss P. C., & Zajac E. J. (2006). The symbolic management of strategic change: Sensegiving via framing and decoupling. *Academy of Management Journal* 49(6), 1173-1193.

Fleming L., & Sorenson O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research policy* 30(7), 1019-1039.

Floetgen R. J., Strauss J., Weking J., Hein A., Urmetzer F., Böhm M., & Krcmar H. (2021). Introducing platform ecosystem resilience: leveraging mobility platforms and their ecosystems for the new normal during COVID-19. *European Journal of Information Systems* 30(3), 304-321.

Fosfuri A., & Tribo J. A. (2008). Exploring the antecedents of potential absorptive capacity and its impact on innovation performance. *Omega-International Journal of Management Science* 36(2), 173-187.

Franke N., & Von Hippel E. (2003). Satisfying heterogeneous user needs via innovation toolkits: the case of Apache security software. *Research policy* 32(7), 1199-1215.

Gimenez R., Labaka L., & Hernantes J. (2017). A maturity model for the involvement of stakeholders in the city resilience building process. *Technological Forecasting and Social Change* 121, 7-16.

Gomez-Mejia L., Wiseman R. M., & Dykes B. J. (2005). Agency problems in diverse contexts: A global perspective. *Journal of Management Studies* 42(7), 1507-1517.

Guo X., Li M., Wang Y., & Mardani A. (2023). Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. *Journal of Business Research* 163, 113868.

Hajli N., Shanmugam M., Powell P., & Love P. E. (2015). A study on the continuance participation in on-line communities with social commerce perspective. *Technological Forecasting and Social Change* 96, 232-241.

Han H., & Trimi S. (2022). Towards a data science platform for improving SME collaboration through Industry 4.0 technologies. *Technological Forecasting and Social Change* 174.

Hanelt A., Bohnsack R., Marz D., & Antunes Marante C. (2021). A Systematic Review of the Literature on Digital Transformation: Insights and Implications for Strategy and Organizational Change. *Journal of Management Studies* 58(5), 1159-1197.

He Z., Huang H., Choi H., & Bilgihan A. (2023). Building organizational resilience with digital transformation. *Journal of Service Management* 34(1), 147-171.

Huang H., Wang C., Wang L., & Yarovaya L. (2023). Corporate digital transformation and idiosyncratic risk: Based on corporate governance perspective. *Emerging Markets Review* 101045.

Ivan Siang-Meng S. I. N., Musa N. A., & Keith Yong-Ngee N. G. (2017). Building Business Resilience through Incident Management Body of Knowledge (IM-BOKTM): The Amalgamated Framework for Total Resilient Capability. *Global Business and Finance Review* 22(1), 38-50.

Jacobides M. G., Cennamo C., & Gawer A. (2018). Towards a theory of ecosystems. *Strategic management journal* 39(8), 2255-2276.

Jiang X., & Yuan Q. (2018). Institutional investors' corporate site visits and corporate innovation. *Journal of Corporate Finance* 48, 148-168.

Khurana I., Dutta D. K., & Ghura A. S. (2022). SMEs and digital transformation during a crisis: The emergence of resilience as a second-order dynamic capability in an entrepreneurial ecosystem. *Journal of Business Research* 150, 623-641.

Konadu R., Owusu-Agyei S., Lartey T. A., Danso A., Adomako S., & Amankwah-Amoah J. (2020). CEOs' reputation, quality management and environmental innovation: The roles of stakeholder pressure and resource commitment. *Business Strategy and the Environment* 29(6), 2310-2323.

Lane P. J., & Lubatkin M. (1998). Relative absorptive capacity and interorganizational learning. *Strategic management journal* 19(5), 461-477.

Linnenluecke M. K. (2017). Resilience in Business and Management Research: A Review of Influential Publications and a Research Agenda. *International Journal of Management Reviews* 19(1), 4-30.

Liu J., Liu S., Xu X., & Zou Q. (2022). Can Digital Transformation Promote the Rapid Recovery of Cities from the COVID-19 Epidemic? An Empirical Analysis from Chinese Cities. *International Journal of Environmental Research and Public Health* 19(6).

Llopi-Albert C., Rubio F., & Valero F. (2021). Impact of digital transformation on the automotive industry. *Technological Forecasting and Social Change* 162.

Makadok R., & Barney J. B. (2001). Strategic factor market intelligence: An application of information economics to strategy formulation and competitor intelligence. *Management Science* 47(12), 1621-1638.

Matarazzo M., Penco L., Profumo G., & Quaglia R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities

perspective. *Journal of Business Research* 123, 642-656.

Matt C., Hess T., & Benlian A. (2015). Digital Transformation Strategies. *Business & Information Systems Engineering* 57(5), 339-343.

Merton R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance* 29(2), 449-470.

Morck R., Yeung B., & Yu W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of financial economics* 58(1-2), 215-260.

Mowery D. C., & Oxley J. E. (1995). Inward technology transfer and competitiveness: the role of national innovation systems. *Cambridge journal of economics* 19(1), 67-93.

Mueller J. M., Buliga O., & Voigt K.-I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change* 132, 2-17.

Oliver C. (1992). The Antecedents of Deinstitutionalization. *Organization Studies* 13(4), 563-588.

Ortiz-de-Mandojana N., & Bansal P. (2016). The long-term benefits of organizational resilience through sustainable business practices. *Strategic Management Journal* 37(8), 1615-1631.

Paolucci E., Pessot E., & Ricci R. (2021). The interplay between digital transformation and governance mechanisms in supply chains: evidence from the Italian automotive industry. *International Journal of Operations & Production Management* 41(7), 1119-1144.

Peress J. (2010). Product Market Competition, Insider Trading, and Stock Market Efficiency. *Journal of Finance* 65(1), 1-43.

Porter M. E., & Heppelmann J. E. (2014). How smart, connected products are transforming competition. *Harvard business review* 92(11), 64-88.

Salovaara A., Lyytinen K., & Penttinen E. (2019). High Reliability in Digital Organizing: Mindlessness, the Frame Problem, and Digital Operations. *Mis Quarterly* 43(2), 555-+.

Salvato C., & Vassolo R. (2018). The sources of dynamism in dynamic capabilities. *Strategic Management Journal* 39(6), 1728-1752.

Sanirs S. C., Liguori E. W., & Garvey E. (2023). How digitalization reinvented entrepreneurial resilience during COVID-19 br. *Technological Forecasting and Social Change* 189.

Serfling M. (2016). Firing Costs and Capital Structure Decisions. *Journal of Finance* 71(5), 2239-2285.

Shashi, Centobelli P., Cerchione R., & Ertz M. (2020). Agile supply chain management: where did it come from and where will it go in the era of digital transformation? *Industrial Marketing Management* 90, 324-345.

Sia S. K., Weill P., & Zhang N. (2021). Designing a Future-Ready Enterprise: The Digital Transformation of DBS Bank. *California Management Review* 63(3), 35-57.

Siachou E., Vrontis D., & Trichina E. (2021). Can traditional organizations be digitally transformed by themselves? The moderating role of absorptive capacity and strategic interdependence. *Journal of Business Research* 124, 408-421.

- Tamym L., Benyoucef L., Moh A. N. S., & El Ouadghiri M. D. (2021). A big data based architecture for collaborative networks: Supply chains mixed-network. *Computer Communications* 175, 102-111.
- Usai A., Fiano F., Petruzzelli A. M., Paoloni P., Briamonte M. F., & Orlando B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research* 133, 327-336.
- Vial G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems* 28(2), 118-144.
- Warner K. S. R., & Waeger M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning* 52(3), 326-349.
- Williams T. A., Gruber D. A., Sutcliffe K. M., Shepherd D. A., & Zhao E. Y. (2017). Organizational response to adversity: Fusing crisis management and resilience research streams. *Academy of Management Annals* 11(2), 733-769.
- Wu F., Hu H., Lin H., & Ren X. (2021). Enterprise digital transformation and capital market performance: Empirical evidence from stock liquidity. *Management World* 37(7), 130-144.
- Wu K., Fu Y., & Kong D. (2022). Does the digital transformation of enterprises affect stock price crash risk? *Finance Research Letters* 48, 102888.
- Yao F. K., & Chang S. (2017). Do Individual Employees' Learning Goal Orientation and Civic Virtue Matter? A Micro-Foundations Perspective on Firm Absorptive Capacity. *Strategic Management Journal* 38(10), 2041-2060.
- Ye F., Ke M., Ouyang Y., Li Y., Li L., Zhan Y., & Zhang M. (2023). Impact of digital technology usage on firm resilience: a dynamic capability perspective. *Supply Chain Management-an International Journal*.
- Yuan R., Luo J., Liu M. J., & Yu J. (2022). Understanding organizational resilience in a platform-based sharing business: The role of absorptive capacity. *Journal of Business Research* 141, 85-99.
- Zhu K., Dong S., Xu S. X., & Kraemer K. L. (2006). Innovation diffusion in global contexts: determinants of post-adoption digital transformation of European companies. *European journal of information systems* 15, 601-616.
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EXPLORING THE IMPACT OF AGILE CAPABILITIES ON DIGITAL TRANSFORMATION SUCCESS

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Keywords: Digital transformation, agile methodologies, technology adoption, PLS-SEM analysis.

Digital transformation refers to the process by which businesses and organizations adopt digital technologies to bring about changes in their business models, processes and customer experience. This process includes the integration of new technologies, but also the revision of business strategies, in order to be aligned with the demands of the digital age. Digital transformation is closely linked to innovation and the ability of businesses to adapt to rapidly changing environments. According to Verhoef and Broekhuizen (2021), digital transformation has radically changed consumer expectations and behaviors and has disrupted many markets. The integration of technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data, blockchain and digital twins can significantly impact the way businesses create and capture value in the marketplace. Digital transformation has become an imperative for most organizations, in a world of constant change (Gong, 2021).

Digital transformation offers multiple benefits in innovation, financial returns, company reputation, growth, and the development and maintenance of competitive advantage (Vial, 2019). Using digital technologies during digital transformation enhances customer engagement and participation and creates loyalty relationships that, in the long term, lead the business to greater profits. Despite the potential benefits offered by digital transformation, adapting existing business models and integrating new technologies may be challenging for traditional businesses, as it requires significant organizational change and strategic renewal (Nadkarni & Prügl, 2021). Successful transition depends largely on the ability of businesses to redefine their core principles and develop new capabilities that will allow them to compete in an ever-changing digital environment. Accordingly, digital transformation success is commonly defined as the achievement of strategic objectives through the effective integration of digital technologies, leading to enhanced organizational performance, customer experience, and innovation capacity (Vial, 2019).

Digital transformation has become an increasingly important issue for Greek businesses, especially over the last few years. In a recent survey conducted in 2022-2023 (Foundation, 2023), it appears that Greece has made progress in its National Digital Strategy, continuously developing next-generation networks and constantly improving its technological talent, but it is still far behind other European countries. According to DESI 2022, it is ranked 26th out of 28 in total in the Digital Economy and Society Index. Greece plans to allocate substantial capital toward digitalization efforts through 2026, positioning itself more favorably than many other European Union countries (Bruegel; Statista, 2023).

Agile methodologies are an umbrella term that covers a variety of frameworks and methods (PMI, 2017). They consist of practices that promote continuous iteration of software development and testing throughout the project lifecycle. They emphasize

collaboration, flexibility and customer satisfaction. Agile methodologies were first designed for software development, but over time, they have been used by many other industries. Agile methodologies can be categorized into five core categories: Scrum, Kanban, Extreme Programming (XP), Lean and Crystal. Among these, Scrum and Kanban have emerged as the most widely adopted approaches by organizations (Ozkan et al., 2022). The agile mindset is defined by values, guided by principles and manifested through many different practices (PMI, 2017). Companies choose the practices they will adopt according to their needs. The agile approach aims to grow the organization that adopts it while supporting other groups, such as development teams within the organization. These teams should act flexibly, adapting to both customer expectations and how their customers operate.

Agile methodologies can be used in the digital transformation process. Applying agile to digital transformation initiatives involves using the agile methodology to manage changes and improvements, which are an integral part of the digital transformation process. Businesses are being urged to adopt agile practices to increase their speed and agility. Agile serves an ideal framework for digital transformation, as it enables rapid iterations driven by customer feedback and leads to a broader cultural change within the organization (Sallam et al., 2024).

The objective of this research is to evaluate the impact of key agile-related capabilities on digital transformation success. Rather than focusing solely on specific agile methodologies, this study examines how dimensions such as agile maturity, agile education, organizational culture, innovation, knowledge, and technology influence the success of digital transformation initiatives. The model explores both direct effects and indirect relationships, highlighting technology's mediating role (Figure 1).

Initially, agile maturity refers to the company's maturity on agile practices adoption and according to literature, there is a significantly strong relationship between agile maturity and the success of digital transformation, as agile practices focus on adaptability and speed (Sallam et al., 2024). Thereafter, agile education relates to employees' training in agile methodologies, as employee training boosts understanding and knowledge of agile. Following this, innovation indicates that companies invest in adaptability and continuous learning, to effectively respond to daily challenges and changes (Vial, 2019). Technology refers to the use of new digital technologies. Literature mentions that technology-related aspects have been established as the building blocks for achieving digital transformation (Desmet et al., 2015). Subsequently, knowledge is a variable in the first phase of the decision-making process in digital transformation and a fundamental factor in the behavioral dimension of an individual (Oh et al., 2022). It relates to the level of experience and understanding of digital technology. Lastly, culture refers to the acceptance of new technologies, the willingness for continuous learning and the strengthening of collaboration between the various departments of the business (Nadkarni & Prügl, 2021).

Ten hypotheses were formulated regarding the relationships among the dimensions of the model and an online questionnaire was created utilizing a 5-point Likert scale (ranging from 1= strongly disagree to 5= strongly agree), with 49 questions addressing the dimensions of agile maturity (Ntandoyethu et al., 2019), agile ed-

ucation (Chen et al., 2016, Koutsikouri et al., 2020, Baxter et al., 2023), culture (Vogelsang et al., 2018, Ntandoyethu et al., 2019), innovation (Rogers, 1995, Son et al., 2019, Ntandoyethu et al., 2019), technology (Ravichandran et al., 2005, Vogelsang et al., 2018, Ntandoyethu et al., 2019), and knowledge (Moore & Benbasat, 1991, Ravichandran et al., 2005, Son et al., 2019).

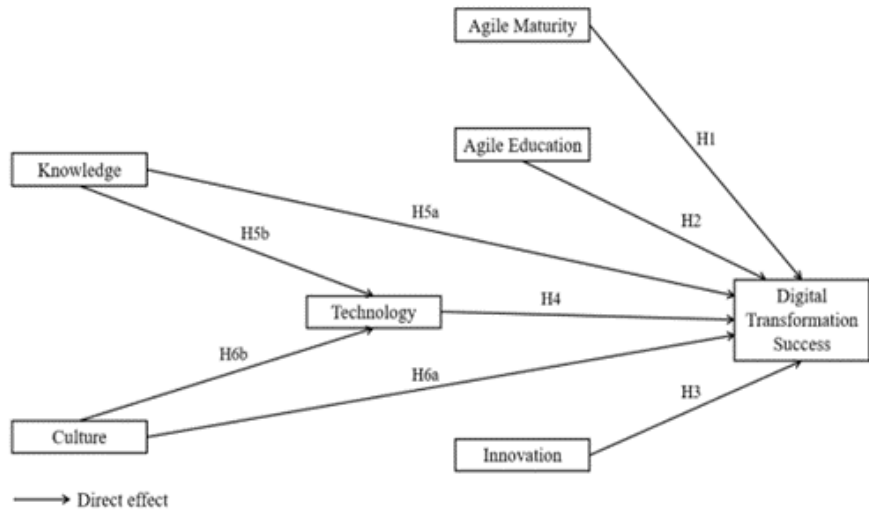


Figure 1: The model

The questionnaire was distributed in Greek, through LinkedIn and e-mail between September and October 2024, to gather data from employees working in a company that has performed digital transformation. The questionnaire was completed by 124 Greek employees. The data were analyzed using partial least square structural equation modeling (PLS-SEM).

The sample revealed several noteworthy findings. A majority of the participants (55%) held a master's degree, 23% occupied managerial positions, either at the first-line or senior level and 59% were employed in organizations with more than 1,000 employees. Furthermore, 77% of the participants reported working within either an agile or hybrid model, while only 4% used the traditional waterfall model; 19% were uncertain about their organization's approach. Additionally, all respondents demonstrated familiarity with digital transformation, as their companies had already undertaken such initiatives, with 59% of those transformations implemented using agile methodologies. In terms of industry representation, the most common sectors among respondents were technology, telecommunications and finance.

The findings of this study suggest that agile education, innovation, technology and agile maturity positively influence the success of digital transformation. While knowledge and culture do not directly influence digital transformation success, they appear to have an indirect effect, with technology serving as a full mediator in this relationship.

The study's results highlight that agile education, innovation, technology, and agility maturity are all significantly vital for digital transformation. Since each of these parameters directly touches upon the capability of the company to adapt and progress in this digital era, emphasizing the importance of fostering an agile mindset, encouraging innovation, and leveraging technological advancements. The

indirect effects of knowledge and culture through technology as a mediator further underline the central role played by technology in digital transformation initiatives. That is to say, knowledge and culture may not immediately affect the successes of transformation but create the building blocks for effective technological integration, whereby success is driven. This interplay underlines the complexity of digital transformation but also makes it important to consider direct and mediated relationships among influencing factors.

Compared to prior studies, which mainly focus on the direct impact of agile methodologies or frameworks (e.g., Scrum, Kanban), this research highlights the importance of broader organizational readiness factors, such as agile maturity and education, in achieving digital transformation success. These findings reveal that while knowledge and culture may not directly affect success, their influence is fully mediated through technology. This underscores the important role of technological integration that acts as a bridge between human factors and digital transformation outcomes, which current studies have not thoroughly investigated.

This study has a few limitations worth noting. First, the sample is restricted to 124 employees from Greek companies undergoing digital transformation, which limits the generalizability of the findings to broader contexts or other countries. Future research may further expand the sample size by respondents from a wider geographical and organizational setting in order to test the cross-border applicability of the model. Second, working with self-reported data raises problems of response bias, as respondents may overstate the capabilities of their organization or the extent to which these capabilities align with digital transformation objectives. Mixed-methods approaches in studies could be used in the future, consisting of interviews or objective organization data, to enhance the internal validity of the findings. Finally, future research could focus on evaluating the challenges and obstacles organizations encounter during the implementation of digital transformation initiatives, as well as the role of technology in addressing these challenges. In particular, it is recommended to examine the effectiveness and suitability of specific technological tools designed to facilitate this process and to identify which of these tools are considered most effective in practice.

References

- Baxter, D., Dacre, N., Dong, H., & Ceylan, S. (2023). "Institutional challenges in agile adoption: Evidence from a public sector IT project". *Government Information Quarterly*, 40(4), 101858.
- Bruegel; Statista (2023). "Digitalization in the EU - NextGenerationEU funds used for digitalization 2021-2026".
- Chen Roger Ronxin, Ravichandar Ramya, Proctor Don. (2016). "Managing the transition to the new agile business and product development model: Lessons from Cisco Systems". *Business Horizons*, 59(6), 635-644.
- DESI. (2020). "Digital Economy and Society Index (DESI) 2022".
- Desmet D., Duncan E., Scanlan J. & Singer M. (2015). "Six building blocks for creating a high-performing digital enterprise". *McKinsey Digital*, 1-8.
- Foundation in collaboration with EIT Digital. (2023). "Digital Transformation in Greece 2022-2023".

Gong, C., & Ribiere, V. (2021). "Developing a unified definition of digital transformation". *Technovation*, 102, 102217.

Koutsikouri Dina, Madsen Sabine, Lindström Nataliya Berbyuk. (2020). "Agile transformation: How employees experience and cope with transformative change". *Agile Processes in Software Engineering and Extreme Programming-Workshops: XP 2020 Workshops*, Copenhagen, Denmark, June 8-12, 2020, Revised Selected Papers 21: Springer International Publishing.

Kyunghwan Oh, Hyeongseog Kho, Youngjin Choi and Seogjun Lee. (2022). "Determinants for Successful Digital Transformation". *Sustainability*, 14, 1215.

Moore, G. C., & Benbasat, I. (1991). "Development of an instrument to measure the perceptions of adopting an information technology innovation". *Information systems research*, 2(3), 192-222.

Nadkarni Swen, Prügl Reinhard. (2021). "Digital transformation: a review, synthesis and opportunities for future research". *Management Review Quarterly*, 71, 233-341.

Ntandoyethu S.M. Mhlungu, Jeff Y.J. Chen, Peter Alkema. (2019). "The underlying factors of a successful organizational digital transformation". *South African Journal of Information Management*, 2078-1865.

Ozkan, N., Bal, S., Erdogan, T. G., & Gök, M. Ş. (2022). "Scrum, Kanban or a mix of both? A systematic literature review". In *2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS)*, IEEE, 883-893.

PMI. (2017). "Agile practice guide". Project Management Institute, Newtown Square, Pa.

Ravichandran T., Lertwongsatien C. and Lertwongsatien C. (2005). "Effect of information systems resources and capabilities on firm performance: A resource-based perspective". *Journal of Management Information Systems*, 21(4), 237-276.

Rogers E.M. (1995). "Diffusion of Innovations". 4th ed.; Free Press: New York, NY, USA, 160-251.

Sallam Sara Hassan Ahmed, Fouad Mohamed Mostafa, Fahd Hemeida. (2024). "Relationship between Agile Maturity and Digital Transformation Success". *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 33(3), 154-168.

Son S.Y., Moon J.W., Yang K.M., Kim S.Y., Park C.H., Hong E.Y., Lee H.J., Song D.S., Park Y.L., Jang M.J. et al. (2019). "Study on the Advancement and Determinants of the Social Acceptability Model of Intelligent Information Technology: Cooperative Study of the Economic and Humanities Society 19-41-02". Korea Information Society Development Institute (KISDI): Chungcheongbuk-do, Korea.

Verhoef Peter, C., Thijs Broekhuizen, Yakov Bartb, Abhi Bhattacharyaa, John Qi Donga, Nicolai Fabiana, Michael Haenlein. (2021). "Digital transformation: A multidisciplinary reflection and research agenda". *Journal of Business Research*, 122, 889-901.

Vial, G. (2021). "Understanding digital transformation: A review and a research agenda". *Managing digital transformation*, 13-66.

Vogelsang, K., Liere-Netheler, K., Packmohr, S., & Hoppe, U. (2018). "Success factors for fostering a digital transformation in manufacturing companies". *Journal of Enterprise Transformation*, 8(1-2), 121-142.

BUSINESS STRATEGIES FOR COMPETITIVE TECHNOLOGICAL ADVANTAGE: A SYSTEMATIC REVIEW ON GAMIFICATION IN METAVERSE

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Keywords: Gamification, metaverse, customer engagement, business value, business strategy.

Introduction

The integration of gamification into the metaverse presents a transformative opportunity for businesses to establish competitive advantages in the digital era. Gamification, defined as the application of game design elements in non-gaming contexts (Deterding et al., 2011), has demonstrated significant potential in enhancing customer engagement, motivation, and business operations across multiple industries (Seaborn & Fels, 2015). The metaverse—an interconnected network of immersive, persistent virtual spaces enabled by AI, blockchain, and extended reality (AR/VR)—offers unprecedented opportunities to revolutionize business strategies by enabling immersive customer interaction and engagement through fostering intrinsic motivation and value-driven interactions. (Lee et al., 2024).

Unlike standalone AR or VR applications, the metaverse seamlessly integrates multiple technologies to create shared, interactive, and dynamic environments where users can engage in real-time interactions across diverse digital platforms (Vidal-Tomás, 2023). This convergence opens new avenues for social interaction and business collaboration, transforming traditional engagement models into more immersive and participatory experiences (Yazıcı et al., 2024). For instance, gamified virtual retail environments can replicate real-world shopping experiences, enhancing customer satisfaction and fostering brand loyalty through personalized, interactive features (Richter & Richter, 2023; Dionisio et al., 2013).

Gamification in the metaverse serves as an innovative business strategy for competitive technological advantage. Businesses leverage gamified experiences to enhance customer retention, improve brand engagement, and optimize monetization models, thereby positioning themselves strategically within the evolving digital ecosystem (Rane et al., 2023; Wasiq et al., 2024; Koivisto & Hamari, 2019).

The global metaverse market, valued at \$82.02 billion in 2024, is projected to grow at a compound annual growth rate (CAGR) of 43.9% between 2024 and 2030 (Grand View Research Report, 2024). However, recent studies caution against overly optimistic projections and highlight challenges such as platform sustainability, monetization constraints, and user retention difficulties (Vidal-Tomás, 2023). Addressing these concerns, this study critically evaluates the current state of metaverse gamification, identifies key opportunities, and proposes future research directions to enhance strategic business applications (Saridakis et al., 2024).

The emergence of the metaverse presents businesses with novel opportunities to gain a competitive edge by adopting innovative engagement strategies. Among these, gamification has been widely recognized as an effective approach for enhancing customer experiences by integrating gamified elements such as loyalty programs,

interactive virtual marketplaces, and AI-driven personalization. (Malik et al., 2024; Harwood & Garry, 2015).

Core gamification mechanisms—such as points, badges, leaderboards, avatars, and challenges—offer structured incentives and a sense of achievement, fostering competition and goal-setting as key drivers of user motivation (Habachi et al., 2023; Hamari et al., 2014).

The effectiveness of these mechanisms is further magnified within the metaverse, where real-time interactivity and persistent digital identities create immersive and dynamic environments for customer engagement (Xi & Hamari, 2020). By strategically embedding gamification within metaverse platforms, businesses can strengthen consumer relationships, brand loyalty, and establish a sustainable competitive advantage (Arya et al., 2023).

We articulate the distinctions between gamification in the metaverse and its applications in virtual worlds, online communities, education, and e-commerce, demonstrating unique affordances of metaverse environments such as real-time interactivity, persistent digital identities, and AI-driven personalization. (Lowry et al., 2025; Khan et al., 2025).

This study systematically reviews the literature at the intersection of gamification and the metaverse to explore their synergistic potential in driving customer engagement and enhancing business value—critical to competitive strategy in AI-driven businesses.

Method and key findings

This study employs a systematic literature review (SLR) methodology, recognized for its rigor and replicability in business and technology research (Tranfield, Denyer & Smart, 2003). Our SLR adheres to established frameworks, ensuring a transparent research process (Azarian et al., 2023; Paul et al., 2023). The SLR follows Kitchenham's three-step process (Kitchenham, 2004) and Webster and Watson's concept-centric framework (Webster & Watson, 2002), ensuring a comprehensive approach to literature analysis.

To strengthen methodological rigor, we have expanded our review scope by incorporating a structured framework that categorizes prior research into three key dimensions. This framework offers a clearer synthesis of existing research and highlights gaps for future studies (Snyder, 2019).

To address this, our study systematically examines these diverse contributions, synthesizing insights from multiple perspectives to provide a coherent understanding of the field. Furthermore, we identify critical knowledge gaps, particularly concerning the role of AI-driven personalization, the long-term effects of gamification on user engagement, and the ethical considerations of data privacy in gamified virtual experiences.

The review was performed by first providing an overall mapping of the literature, then extracting insights and categorizing findings through open coding to identify primary themes and axial coding to group them into overarching categories and finally, suggesting future research directions based on the review findings.

The **findings of the literature analysis** are clustered into the following thematic sections:

1. **Theoretical Foundations:** This review identifies key theories that underpin gamification in the metaverse, such as self-determination theory (Deci & Ryan, 1985; Yang et al., 2024), flow theory (Csikszentmihalyi, 1990), game theory (Favero et al., 2024), Theory of work gamification, social presence theory, social exchange theory (STP), communication theory, cognitive load theory, biased competition theory, selective attention theory, and information theory (Krath et al., 2021). These frameworks provide insights into how gamified mechanics, such as rewards, points, and challenges, drive user engagement and motivation (Sailer et al., 2017).
2. **Gamification Mechanisms in the Metaverse:** This section classifies **gamification strategies** into three primary categories:
 - **Behavioral Gamification:** Utilizing motivational triggers such as rewards and social validation to influence user behavior (Bassanelli et al., 2022; Ourdas & Ponis, 2023).
 - **Structural Gamification:** Embedding game mechanics into existing systems or processes to enhance productivity and efficiency, such as in corporate training programs (Gerdenitsch et al., 2020; Hosseini et al., 2022).
 - **Content Gamification:** Employing narrative and storytelling techniques to increase cognitive engagement in digital marketing (Rasmusson, 2017; Ertemel, 2021; Christopoulos & Mystakidis, 2023).
3. **Impact of Metaverse Gamification on Business strategies:** This review synthesizes empirical evidence on how gamification, powered by AI and VR technologies, is transforming customer engagement and brand loyalty across various business domains (Latino et al., 2024; Kumar et al., 2025). For instance, gamified virtual showrooms have been shown to significantly enhance user engagement and drive business value (Hamari, Koivisto & Sarsa, 2014). However, research cautions that an over-reliance on gamification, without a well-structured engagement strategy, may lead to diminishing user retention (Hatami et al., 2024; Benjamins et al., 2023). Additionally, metaverse designers face challenges in sustaining user engagement and ensuring long-term interaction, as participants often struggle with motivation and value realization in gamified environments (Dwivedi et al., 2022).

Conclusion and future research directions

While gamification has been extensively studied in digital platforms, its applications within the metaverse lack a systematic theoretical foundation. This paper addresses this gap by synthesizing existing research and proposing a structured research agenda.

Key research gaps include:

1. The role of AI-driven personalization in metaverse-based gamification.
2. Ethical considerations surrounding data privacy and security in gamified virtual environments remain underexplored and warrant further investigation.

3. The integration of gamification with blockchain technologies to ensure decentralization and security.
4. Longitudinal studies investigating the long-term effects of gamification on consumer behavior and brand loyalty in immersive digital spaces (Hatami et al., 2024; Benjamins et al., 2023; Kumar, 2024).

By elucidating emergent themes and research gaps, this study contributes a robust conceptual framework for both academics and practitioners. It provides a forward-looking research agenda that guides future investigations into the strategic application of gamification within digital ecosystems.

As businesses increasingly integrate gamification into their metaverse strategies, understanding its impact on user behavior, brand loyalty, and market competitiveness becomes crucial. Our analysis not only enhances theoretical discussions but also provides actionable insights for organizations aiming to leverage gamification as a strategic tool in digital ecosystems.

This paper synthesizes and critically evaluates contemporary scholarship while charting a forward-looking research agenda to address extant research limitations. The findings reveal how gamification fosters dynamic, reward-driven virtual environments that seamlessly integrate physical and digital experiences, enabling businesses to cultivate deeper consumer connections and leverage data-driven decision-making. The review traces the evolution of gamification paradigms and examines the synergistic interplay between gamification strategies and foundational metaverse technologies. The findings make a substantive contribution to the information systems discipline, offering a robust theoretical and practical foundation for advancing the strategic application of gamification within virtual environments and broader digital ecosystems.

We have strengthened this rationale by extensively analyzing the growing body of research on gamification in the metaverse, which has seen a significant increase in scholarly attention in recent years. The expanding literature highlights both the potential and challenges associated with implementing gamification strategies in immersive virtual environments, yet remains fragmented across various disciplines and application areas (Thomas et al., 2023; Sharma et al., 2024).

Ultimately, this paper advances our understanding of how immersive, gamified environments can be strategically leveraged to enhance business value and customer engagement and how businesses can harness the power of gamification in the metaverse to drive customer engagement, enhance business value, and achieve sustainable competitive advantages.

References

- Arya, V., Sambyal, R., Sharma, A., & Dwivedi, Y. K. (2023). Brands are calling your avatar in metaverse: A study to explore XR-based gamification marketing activities and consumer-based brand equity in the virtual world. *Journal of Consumer Behaviour*, 23(2), 556-585.
- Azarian, M., Yu, H., Shiferaw, A. T., & Stevik, T. K. (2023). Do we perform systematic literature review right? A scientific mapping and Methodological Assessment. *Logistics*, 7(4), 89.

Bassanelli, S., Vasta, N., Bucchiarone, A., & Marconi, A. (2022). Gamification for behavior change: A scientometric review. *Acta Psychologica*, 228, 103657.

Benjamins, R., Rubio Viñuela, Y., & Alonso, C. (2023). Social and ethical challenges of the metaverse. *AI and Ethics*, 3(3), 689-697.

Christopoulos, A. & Mystakidis, S. (2023). Gamification in education, *Encyclopedia*, 3(4), 1223-1243.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. Harper & Row.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic Motivation and Self-Determination in Human Behavior*. New York: Plenum Press., PP.11-40.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, PP. 9-15.

Dionisio, J.D.N., Burns, W.G. and Gilbert, R. (2013). 3D Virtual worlds and the Metaverse: Current status and future possibilities. *ACM Computing Surveys*, 45(3), 1-38.

Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete. (2022). Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 66, 102542.

Ertemel, A.V. (2021). *Illusional Marketing: The Use of Storytelling, User Experience, and Gamification in Business*. Lincoln: Zea Books. Lincoln, NE.

Favero, M., Schiavo, C., Verzotto, L., Buratto, A., Marchioro, T., & Badia, L. (2024). Strategic cooperation in the metaverse: A game theory analysis with age of information. *International Wireless Communications and Mobile Computing Conference (IWCMC)*, 1466-1471.

Gerdenitsch, C., Sellitsch, D., Besser, M., Burger, S., Stegmann, C., Tscheligi, M., & Kriglstein, S. (2020). Work gamification: Effects on enjoyment, productivity and the role of leadership. *Electronic Commerce Research and Applications*, 43, 100994.

Grand View Research. (2024). *Robotic Process Automation (RPA) Market Size, Share & Trends Analysis Report*. [Report]. Available at: <https://www.grandviewresearch.com/industry-analysis/robotic-process-automation-rpa-market#:~:text=Robotic%20Process%20Automation%20Market%20Trends,43.9%25%20from%202025%20to%202030> (Accessed: 10 February 2025).

Habachi, S., Matute, J. and Palau-Saumell, R. (2023) Gamify, engage, build loyalty: Exploring the benefits of gameful experience for branded sports apps. *Journal of Product & Brand Management*, 33(1), 57-75.

Hamari, J., Koivisto, J. and Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. *Proceedings of the 47th Hawaii International Conference on System Sciences (HICSS)*, 3025-3034.

Harwood, T., & Garry, T. (2015). An investigation into gamification as a customer engagement experience environment. *Journal of Services Marketing*, 29(6/7), 533-546.

Hatami, M., Qu, Q., Chen, Y., Kholidy, H., Blasch, E., & Ardiles-Cruz, E. (2024). A Survey on Real-Time Metaverse: Challenges and Opportunities. *Future*

Internet 2024, 16(10), 379.

Hosseini, C., Humlung, O., Fagerström, A., & Haddara, M. (2022). An experimental study on the effects of gamification on Task Performance. *Procedia Computer Science*, 196, 999-1006.

Khan, Y. F., Mir, B., & Koundal, D. (2025). The metaverse beyond the hype: Interdisciplinary perspectives on applications, tools, techniques, opportunities, and challenges of the metaverse. *Exploring the Metaverse*, 213-223.

Kitchenham, B. (2004). Procedures for performing systematic reviews. Keele University, Technical Report, TR, 1-33.

Koivisto, J. and Hamari, J. (2019) The rise of Motivational Information Systems: A review of Gamification Research. *International Journal of Information Management*, 45, 191-210.

Krath, J., Schürmann, L., & von Korflesch, H. F. O. (2021). Revealing the theoretical basis of gamification: A systematic review and analysis of theory in research on gamification, serious games and game-based learning. *Computers in Human Behavior*, 125, 106963.

Kumar, A., Shankar, A., Behl, A., Pereira, V., Kapoor, P., & Papa, A. (2025). Implementing enterprise metaverse as a means of enhancing growth hacking performance: Will adopting the metaverse be a success in organizations? *Journal of Business Research*, 188, 115079.

Kumar, H. (2024) Virtual worlds, real opportunities: A review of marketing in the metaverse. *Acta Psychologica*, 250, 104517.

Latino, M. E., De Lorenzi, M. C., Corallo, A., & Petruzzelli, A. M. (2024). The impact of Metaverse for Business Model Innovation: A review, novel insights and research directions. *Technological Forecasting and Social Change*, 206, 123571.

Lee, L.-H., Braud, T., Zhou, P. Y., Wang, L., Xu, D., Lin, Z., Kumar, A., Bermejo, C., & Hui, P. (2024). All One needs to know about metaverse: A complete survey on Technological Singularity, virtual ecosystem, and Research Agenda. *Foundations and Trends in Human-Computer Interaction*, 18(2-3), 100-337.

Lowry, P. B., Boh, W. F., Petter, S., & Leimeister, J. M. (2025). Long Live the Metaverse: Identifying the Potential for Market Disruption and Future Research.

Malik, G., Pradhan, D., & Rup, B. K. (2024). Gamification and customer brand engagement: A review and future research agendas. *Marketing Intelligence & Planning*, 43(1), 210-239.

Ourdas, C. and Ponis, S. (2023) Evaluating the effects of gamification in behavioural change: A proposed SEM-based approach. *Sustainability*, 15(6), 5442.

Paul, J., Khatri, P., & Kaur Duggal, H. (2023). Frameworks for developing impactful systematic literature reviews and theory building: What, why and how? *Journal of Decision Systems*, 33(4), 537-550.

Rane, N., Choudhary, S., & Rane, J. (2023). Metaverse for enhancing customer loyalty: Effective strategies to improve customer relationship, service, engagement, satisfaction, and experience. *SSRN Electronic Journal*.

Rasmusson, T. (2017) Interactive storytelling, gamification and online education: Storytelling made easy. *International Journal on Innovations in Online Education*.

Richter, S., & Richter, A. (2023). What is novel about the metaverse? *International Journal of Information Management*, 73, 102684.

- Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior*, 69, 371-380.
- Saridakis, G., Khan, Z., Knight, G., Idris, B., Mitra, J., & Khan, H. (2024). A look into the future: The impact of metaverse on traditional theories and thinking in international business. *Management International Review*, 64(4), 597-632.
- Seaborn, K., Fels, D.I. (2015) Gamification in theory and action: A survey. *International Journal of Human-Computer Studies*, 74, 14-31.
- Sharma, W., Lim, W. M., Kumar, S., Verma, A., & Kumra, R. (2024). Game on! A state-of-the-art overview of doing business with gamification. *Technological Forecasting and Social Change*, 198, 122988.
- Snyder, H. (2019) Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333-339.
- Thomas, N. J., Baral, R., Crocco, O. S., & Mohanan, S. (2023). A framework for gamification in the Metaverse Era: How Designers Envision Gameful Experience. *Technological Forecasting and Social Change*, 193, 122544.
- Tranfield, D., Denyer, D. and Smart, P. (2003) Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207-222.
- Vidal-Tomás, D. (2023) The illusion of the metaverse and meta-economy. *International Review of Financial Analysis*, 86, 102560.
- Wasiq, M., Bashar, A., Khan, I., & Nyagadza, B. (2024). Unveiling customer engagement dynamics in the metaverse: A retrospective bibliometric and topic modelling investigation. *Computers in Human Behavior Reports*, 16, 100483.
- Watson, R.T. and Webster, J. (2002) Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, 26(2), 129-147.
- Xi, N., & Hamari, J. (2020). Does gamification affect brand engagement and equity? A study in online brand communities. *Journal of Business Research*, 109, 449-460.
- Yang, W., Fang, M., Xu, J., Zhang, X., & Pan, Y. (2024). Exploring the mediating role of different aspects of learning motivation between metaverse learning experiences and Gamification. *Electronics*, 13(7), 1297.
- Yazıcı, A.M., Özkan, A. and Özkan, H. (2024) Meta: XR-ar-mr and Mirror World Technologies Business impact of metaverse. *Journal of Metaverse*, 4(1), 21-32.

IT CAPABILITIES, DIGITAL TRANSFORMATION, RESILIENCE AND PERFORMANCE IN ELDERLY CARE UNITS: A CONFIGURATIONAL APPROACH

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Keywords: IT capabilities, digital transformation, organizational resilience, organizational performance, fsQCA.

This research adopts a configurational approach and utilizes fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine how IT capabilities, digital transformation, organizational resilience, and other organization-specific attributes jointly contribute to performance outcomes in Elderly Care Units (ECUs) in Greece. Organizational resources and capabilities are expected to explain organizational performance of ECUs while differing among other contextual factors (Wu and Wu, 2013). Given the unique challenges of the Elderly Care Units (ECUs) sector in Greece, including operating under economic pressure and changing social welfare policies, it is critical to understand the pathways to high or low organizational performance.

Greece suggests an interesting case, since its rapidly aging population has created an urgent need for long-term care services, making ECUs a vital sector for both social welfare and economic stability. The country's ECU landscape is diverse, comprising 300 units that include 152 for-profit, 127 non-profit, and 21 public organizations (Salavou et al., 2024). These organizations take on different legal forms and face specific pressures of economic instability, insufficient government support and a changing social environment (Lamnisos et al., 2021). The diversity of ECUs in Greece provides an excellent context to study the interplay between organizational resources and performance, within the frameworks of the Resource Based View (RBV) and the Dynamic Capabilities View (DCV) theories.

The RBV serves as the key lens through which ECU performance is examined by means of resources that are valuable, rare, inimitable, and non-substitutable (Wernerfelt, 1984). As critical resources in this context, IT capabilities include investments in robust IT infrastructure, frequent upgrades of systems, and develop skilled personnel and need to be maintained at a given level (Bharadwaj, 2000, Chakravarty et al., 2013). An effectively deployed set of these capabilities can streamline operations, improve service quality, and give a competitive edge (Trieu et al., 2023). For example, IT systems that integrate patient health records, automate scheduling, or improve the fast response to an emergency, are instrumental in achieving operational and societal outcomes (Nwankpa and Roumani, 2016). However, IT capabilities are not enough in dynamic environments, especially in environments where there is a need for adaptability, such as elderly care.

The RBV is extended by the DCV theory by stressing the need to reconfigure resources in response to external changes (Teece et al., 1997). Digital transformation is a dynamic capability that allows ECUs to be adaptive to ever-changing demands and resilient. In this study, digital transformation is conceptualized as the use of

digital technologies across organizational processes, for example online platforms for patient engagement, automated monitoring systems for the elderly care, and digital tools for staff training. These technologies not only increase operational efficiency but also allow ECUs to be innovative and to react to crises, such as the COVID-19 pandemic (Chakravarty et al., 2013, Westerman et al., 2014). ECUs frequently embed digital solutions within their operations to more easily deal with the complexity of regulatory necessities, resource limitations, and evolving patient requirements (Pekkarinen et al., 2019). Organizational resilience is defined both passively, as the ability to quickly recover from sudden crises (Somers, 2009), and actively, as a deliberate effort to strengthen preparedness, mitigate potential threats, and ensure long-term survival and success (Trieu et al., 2023). Resilience is seen as the capability to overcome risks and capitalize on opportunities shaped by vulnerabilities, which are influenced by their institutional context and resource dependencies (COVIELLO, 2023, Wulandhari et al., 2022). Within the DCV framework, resilience represents a key dynamic capability that allows ECUs to reconfigure their resources, enabling continuous adaptation and innovation in response to external pressures and environmental changes.

fsQCA is as a methodological tool that uncovers multiple causal configurations (known as equifinality) in which different combinations of conditions can lead to the same outcomes (Douglas et al., 2020). Unlike regression-based approaches that assume linear relationships and additive effects, fsQCA is able to explore complex interdependent relationships between conditions and the fact that the same outcome can come from different pathways (Liu et al., 2017). This configurational approach is especially useful for understanding contexts such as ECUs, where organizational performance results from a dynamic interplay of resources, capabilities, and contextual factors. fsQCA captures these non-linear interactions and identifies unique combinations of conditions causing high or low performance, thus providing a more in-depth understanding of the mechanisms driving organizational success. Data collection was conducted in 2024 using a structured questionnaire designed with Qualtrics. The survey targeted members of the top management team in ECUs across Greece to ensure robust and comprehensive data. The questionnaire was administered during interviews, allowing respondents to provide precise and reliable information. IT capabilities are measured with items, which include investments in IT infrastructure, regular updates, and the degree of alignment of IT skills with industry standards (Trieu et al., 2023). Digital transformation is evaluated with items that reflect the degree to which ECUs incorporate digital technologies into their operations and strategic initiatives (Nwankpa and Roumani, 2016). Organizational resilience is measured along two dimensions: precursor and improvisation resilience (Wang et al., 2023). Organizational-level performance is measured using a scale adopted by Miles et al. (2014) and Pinheiro et al. (2021).

A total of 59 ECUs participated in our study, representing approximately 20% of the total population in Greece. Of these, 23.73% have been operating for up to 10 years, whereas 32.20% have a presence of over 50 years. Regarding their geographical distribution, 74.58% are located in urban areas. In terms of size, 8.47% are classified as very small enterprises, 76.27% as small-sized, and the remaining as medium-sized enterprises.

A necessity analysis based on data calibration revealed that none of the conditions or their absence reached the required consistency threshold of 0.90 for determining necessity in outcome measurement. The truth table analysis revealed three separate configurations that produced high organizational performance while four other configurations resulted in low performance. The essential role of organizational resilience became evident in all paths to high-performance since it enabled ECUs to succeed in complex resource-limited situations.

The results indicate that the combination of advanced digital transformation and strong IT capabilities with organizational resilience became necessary for newer units to achieve high performance. Older and larger ECUs achieved comparable results without requiring significant IT or digital initiatives, which demonstrates that established organizational maturity along with scale can make up for technological investments in particular circumstances.

This study makes several theoretical contributions. First, it extends the RBV theory by incorporating new capabilities, such as digital transformation and organizational resilience, to better explain differences in performance outcomes, particularly the pathways that lead to high versus low performance. By emphasizing these dynamic capabilities, the study bridges the RBV with the DCV, highlighting the importance of resource reconfiguration and adaptation in complex and resource-constrained environments like Elderly Care Units (ECUs). Second, it shows how fuzzy-set Qualitative Comparative Analysis can be used to analyze organizational performance. In contrast to traditional linear methods, fsQCA explicates the configurational nature of performance by identifying multiple pathways to performance, demonstrating that similar outcomes can be produced through different combinations of conditions (Fiss, 2011). The advantage of this approach is that it offers a richer view of the interaction between resource configurations and other factors in shaping performance. Third, it provides new empirical evidence on the RBV and DCV by applying them to the context of ECUs, a neglected but crucial area of strategic management. The results offer a more context-sensitive application of these theories and highlight how organizations in the long-term care sector combine their resources and capabilities to achieve operational efficiency.

The study offers practical implications as well. ECU managers can use the results to allocate resources to IT infrastructure and digital technology investments that lead to both operation efficiency and resilience. In addition, the study reveals that location, age, and size are contextual factors that can affect the effectiveness of resource deployment. Policymakers are also encouraged on their side to support the digital transformation initiatives and to provide targeted funding to strengthen the capacity of ECUs in different regions and legal forms.

This research is not without limitations. First, the data were collected solely from ECUs in Greece, thus restricting the generalizability of the findings to other contexts or countries with different regulatory, economic, and cultural environments. Second, the data is cross-sectional and therefore cannot capture the impact of IT capabilities, digital transformation, and organizational resilience on performance over time. These limitations can be addressed in future research by using longitudinal data, by having a larger study including ECUs in other countries, and by including further qualitative insights to complement the quantitative findings.

References

- Bharadwaj, A. S. (2000), "A resource-based perspective on information technology capability and firm performance: an empirical investigation", *MIS Quarterly*, 169-196.
- Chakravarty, A., Grewal, R. and Sambamurthy, V. (2013), "Information technology competencies, organizational agility, and firm performance: Enabling and facilitating roles", *Information systems research* 24 (4), 976-997.
- COVIELLO, N. (2023), "Weathering a Crisis: A Multi-Level Analysis of Resilience in Young Ventures", *Entrepreneurship Theory and Practice* 47 (3).
- Douglas, E. J., Shepherd, D. A. and Prentice, C. (2020), "Using fuzzy-set qualitative comparative analysis for a finer-grained understanding of entrepreneurship", *Journal of Business Venturing* 35 (1), 105970.
- Fiss, P. C. (2011), "Building better causal theories: A fuzzy set approach to typologies in organization research", *Academy of Management Journal* 54 (2), 393-420.
- Lamnisis, D., Giannakou, K. and Jakovljevic, M. (2021), "Demographic forecasting of population aging in Greece and Cyprus: one big challenge for the Mediterranean health and social system long-term sustainability", *Health Research Policy and Systems* 19, 1-8.
- Liu, Y., Mezei, J., Kostakos, V. and Li, H. (2017), "Applying configurational analysis to IS behavioural research: a methodological alternative for modelling combinatorial complexities", *Information Systems Journal* 27 (1), 59-89.
- Miles, M. P., Verreynne, M.-L. and Luke, B. (2014), "Social enterprises and the performance advantages of a Vincentian marketing orientation", *Journal of Business Ethics* 123, 549-556.
- Nwankpa, J. K. and Roumani, Y. (2016), "IT capability and digital transformation: A firm performance perspective".
- Pekkarinen, S., Melkas, H. and Hyypiä, M. (2019), "Elderly care and digital services: Toward a sustainable sociotechnical transition", *Human-Centered Digitalization and Services*, 259-284.
- Pinheiro, P., Daniel, A. and Moreira, A. (2021), "Social enterprise performance: The role of market and social entrepreneurship orientations", *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations* 32 (1), 45-60.
- Salavou, H., Georgiou, A., Kyriakopoulos, P., Mamakou, X. J., Petropoulou, E., Protonotariou, E. and Sofikitis, E. (2024), "Short mapping report: An integrated mapping of the elderly care units in Greece".
- Somers, S. (2009), "Measuring resilience potential: An adaptive strategy for organizational crisis planning", *Journal of contingencies and crisis management* 17 (1), 12-23.
- Teece, D. J., Pisano, G. and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal* 18 (7), 509-533.
- Trieu, H. D., Van Nguyen, P., Nguyen, T. T., Vu, H. M. and Tran, K. (2023), "Information technology capabilities and organizational ambidexterity facilitating organizational resilience and firm performance of SMEs", *Asia Pacific Management Review* 28 (4), 544-555.

Wang, J., Xue, Y. and Yang, J. (2023), "Can proactive boundary-spanning search enhance green innovation? The mediating role of organizational resilience", *Business Strategy and the Environment* 32 (4), 1981-1995.

Wernerfelt, B. (1984), "A resource-based view of the firm", *Strategic Management Journal* 5 (2), 171-180.

Westerman, G., Bonnet, D. and McAfee, A. (2014), *Leading digital: Turning technology into business transformation*, Harvard Business Press.

Wu, J. and Wu, Z. (2013), "Firm capabilities and the performance in regional polarization", *Management Decision* 51 (8), 1613-1627.

Wulandhari, N. B. I., Gölgeci, I., Mishra, N., Sivarajah, U. and Gupta, S. (2022), "Exploring the role of social capital mechanisms in cooperative resilience", *Journal of Business Research* 143, 375-386.

Session D2

FROM STARTUP TO SCALEUP A Panel Roundtable Discussion

Chair: George Doukidis, Athens U of Economics and Business, Greece

FROM STARTUP TO SCALEUP A Panel Roundtable Discussion

Moderator:

- **Dr. George Doukidis**, Professor in the Department of Management Science and Technology at the Athens University of Economics and Business. Dr. Doukidis's expertise lies in digital innovation and entrepreneurship, innovation in supply chain management, digital transformation and eBusiness, and decision making and artificial intelligence.

Panel members:

1. **Mr. Byron Nicolaides**, Founder and CEO PeopleCert. He is a visionary entrepreneur and global leader in digital skills development, renowned for founding PeopleCert.
2. **Dr. Haris Lambropoulos**, Assistant Professor in the Department of Educational Sciences and Social Work at the University of Patras, and Chairman of the Hellenic Development Bank of Innovation. His research interests focus on the Economics of Education and Human Resource Development.
3. **Mr. Panayiotis Carabinis**, Managing Director of Endeavor Greece, with a background in financial and banking management and a strong track record in supporting high-impact entrepreneurs and building global entrepreneurial communities.
4. **Dr. Katerina Pramadari**, Professor at the Department of Management Science and Technology at the Athens University of Economics and Business, and Partner Unifund. Her expertise lies in supply chain collaboration, e-business integration, and RFID technologies

Abstract:

This panel will focus on the critical success factors that enable a startup to realise their growth potential including: innovative products, sizeable market, organizational readiness, proper capital, accessible distribution channels, managerial expertise and appropriate human capital, international expansion, healthy financials etc.

Session A3

**TEAMS, COLLABORATION AND
KNOWLEDGE DYNAMICS**

**Chair: Edeltraud Hanappi-Egger, WU Vienna University of Business
and Economics, Austria**

STRENGTHENING MEMBERS' PARTICIPATION: BENEFITS AND TRAPS OF ONLINE-CONSULTATIONS IN SOCCER CLUBS

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Vienna University of Business and Economics, Austria

Keywords: Soccer club, participation, online consultation, stakeowners.

Members' owned soccer clubs are characterized by the fact that they have a strong say in the club's decision making. Not only that, they vote for their board members, who must justify many of their decisions in the annual general assemblies. Structural changes in most cases can be made by a two third majority approval only. Given the fact that most members' owned soccer clubs have thousands of members – e.g., FC Bayern Munich has more than 380.000 and even SC Rapid as the biggest Austrian Club has around 24.000 members, the question is how the involvement of as many members as possible can be realized. Since face-to face meetings are not an adequate place to have in-depth discussions of severe topics and only a low percentage can (or want) join these meetings, alternative ways of participation and involvement must be found. Furthermore, members of soccer clubs are mainly men, only about 10% of women are members in the clubs, although they are committed supporters of soccer. As the European Club Association (2023) showed 59% of so called “tag alongs” (fans attending soccer games just in favor of somebody) are women, but already 34% of club loyalists are women (ECA 2023). Club loyalists are often members and therefore also part of the clubs' governance. These statistics indicate that more and more women are interested in soccer and but are less formally involved in a club's governance and therefore in sport management.

In members' club, which means that members own also 100% of the business, i.e., the financial basis, the future development of the soccer club depends completely on its members. Having only few women there means that the female voice often is not heard. The face-to-face general assemblies are dominated by men, in particular active fans who are highly mobilizing within their groups when it comes to decision making of strategically important topics. Very often they dominate the discussion, and many other opinions are not heard. In terms of the quality of a decision with a high impact on the club, it is important to include a variety of perspectives and to listen to many different opinions.

Thus, the question is, if online participation tools can help to strengthen groups with less power in soccer clubs and to broaden the knowledge base of decision making by including a wide opinion spectrum. Given the impossibility to host all members in face-to-face meetings, online consultation seems to only way to allow as many members as possible to participate in structural decision making. The paper will present the case of SC Rapid, where in 2023 a huge change of the statutes was initiated. To involve diverse members an online consultation was implemented allowing more people to comment and critically reflect on the new statutes. The result was a deep (and very objective) online discussion of emotionally important topics. The critical points could be identified, and compromises could be found. At the end the proposed changes of the statutes were approved by 99,5% of the members. How-

ever, the example also showed the limitations of online participation tools: minority groups are not necessarily strengthened, technologically less capable people might be excluded, there are many non-related comments, and the lack of trust in technology prevent people to join in.

The paper will use theories of power to discuss the pros and cons of such online consultations. Soccer clubs are considered as complex organizations since members and fans are highly committed and emotional when it comes to impactful decisions. Therefore, the traditional stakeholder approach will be further developed to a stake- owner approach including aspects of shared responsibility and commitment in a club's governance (Hanappi-Egger 2024).

References

ECA (2023). Fan of the Future. Defining Modern Football Fandom. ECA_FAN OF THE FUTURE_paper_einzeiler_Clubs.indd (31st January 2025).

Hanappi-Egger, E. (2024). Passion and Profit. Wiesbaden: Springer.

KNOWLEDGE SPILLOVERS IN DIGITAL AND HYBRID TEAMS: A SYSTEMATIC REVIEW AND A FUTURE RESEARCH AGENDA

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Keywords: Knowledge transfer, remote work teams, digital collaboration, systematic review.

Background

Accelerated by the pandemic, the adoption of remote and hybrid work arrangements has become a new reality for organizations. This shift has fundamentally transformed the nature of teamwork and influenced the organizational knowledge transfer processes. Emerging factors that include geographic dispersion of work teams, increased reliance on technology, greater flexibility and autonomy of employees, and the interplay between face-to-face and virtual communication challenge traditional assumptions about organizational knowledge flows and pose unique management challenges. Such factors highlight the need for a deeper understanding of how knowledge is created, transferred, disseminated, and possibly attenuated within digital and hybrid organizational contexts. Through a systematic literature review, we aim to synthesize theoretical perspectives around knowledge spillover dynamics in digital and hybrid work teams, identify key themes in knowledge management, and propose directions for future research.

Rationale

Research on remote teamwork and collaboration has expanded significantly, paralleled by scholarship on knowledge transfer within and across organizations. However, current literature lacks a systematic integration of the antecedents, mechanisms, and outcomes of knowledge transfer in remote and hybrid work teams. This research aims to address this gap by systematically synthesizing various dimensions relating to knowledge transfer (or knowledge spillover) phenomena in these evolving team structures. In addition, we examine the implications of workforce trends that lead to knowledge stagnation, including phenomena such as 'the Great Resignation'. Moreover, contributing to the growing management literature on the dynamics of remote work, we propose a detailed research agenda with several topics to advance our understanding of knowledge transfer in remote and hybrid organizational contexts.

Methods

This research follows the systematic literature review methodology exemplified by Sauer and Seuring (2023) and Tranfield et al. (2003). For our search process, we employed a pre-determined algorithm to identify relevant studies in the Scopus and Clarivate's Web of Science databases, including both journal articles and grey literature, such as conference proceedings and dissertations. Our algorithm combined terms that describe knowledge transfer processes (such as knowledge transfer, spillovers, mobilization, and diffusion) and terms that describe remote and hybrid

working configurations (such as virtual, remote, hybrid, and online teams, telecommuting, and remote or hybrid work). The process was guided by explicit inclusion and exclusion criteria. As per our criteria, we excluded single-organization studies, those narrowly focused on the use of specific technological tools, and non-English language publications. To facilitate abstract screening, we used Rayyan, a web-based tool, with the two authors working independently. Following this, we screened the full text of articles and made further exclusions. Our final sample consists of 39 sources published between 2003 and 2024. The main themes that we identified relate to a) the influence of team structure and team dynamics on remote knowledge spillovers, b) knowledge loss and stagnation, c) the enabling role of technology, and d) team-level or organization-level practices for knowledge management. We extracted and coded relevant data from each source along with bibliometric information. Subsequently, we synthesized and presented evidence.

Findings

Our review yields several important findings. First, we find that virtual and hybrid settings pose challenges in knowledge transfer, especially with regards to tacit knowledge, which is the type of knowledge that cannot be easily codified and is primarily shared via face-to-face interactions (Willson et al., 2024; Shepherd and Cooper, 2020; Kögl and Silvius, 2016). Moreover, technological infrastructure has been highlighted in literature as a crucial enabling factor in knowledge transfer within virtual teams (e.g., Fang et al., 2022; Tietz and Werner, 2022). Also, our sample of included articles mentions the role of specific organizational strategies and practices to enhance knowledge transfer in virtual settings; these include efficient human capital utilization (Serenko, 2022), situational awareness-building (Faraco et al., 2021), and storytelling (Wende et al., 2015). Finally, multiple studies underscore the role of trust for enhancing knowledge transfer processes in virtual settings (e.g., Shepherd and Cooper, 2020; Staples and Webster, 2008).

Theoretical contributions

To our knowledge, this is the first piece of research in the post-pandemic era that synthesizes evidence on knowledge spillovers in digital and remote teams. Through our review, we make four main theoretical contributions. First, we systematically map and integrate existing insights on remote knowledge spillover processes, thus advancing our understanding of these phenomena. Also, we examine several team-level factors that influence knowledge transfer effects, including structural team attributes. Then, we underscore various strategies, techniques, and specific resources that organizations use to enhance knowledge flows in hybrid and remote work settings. Finally, we propose several themes for future research; these themes include the influence of different leadership styles in enhancing knowledge transfer in remote teams, the impact of culture on effective knowledge transfer, the relationship between remote knowledge spillovers and organizational innovation outcomes, and the generational and demographic differences that may facilitate or hinder knowledge spillovers.

Practical implications

Based on our systematic review, we offer a number of recommendations to managers and organizations to enhance knowledge transfer processes in virtual and hybrid teams. First, we recommend that managers build a supportive climate in their teams that emphasizes trust. Additionally, in response to post-pandemic work configurations, managers should create opportunities for informal interaction in order to enhance the transfer of tacit knowledge within remote and hybrid teams. What is more, organization-wide interventions like the creation of e-mentoring programs can be beneficial. Also, organizations should invest in the adoption of digital collaboration tools and train remote workers on their effective utilization. Finally, in relation to employee turnover, we highlight that organizations should devise specific human resource strategies that concentrate on retaining organizational knowledge.

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References

- Fang, Y., Neufeld, D. and Zhang, X., 2022. Knowledge coordination via digital artefacts in highly dispersed teams. *Information Systems Journal*, 32(3), pp.520-543.
- Faraco, R.M., Cordeiro, C.V.C. and Duarte, F.J.D.C.M., 2021, May. Integrated Operations in Times of Pandemic: Communication at Distance and Knowledge Sharing. In *Congress of the International Ergonomics Association* (pp. 131-138). Cham: Springer International Publishing.
- Kögl, S. and Silvius, G., 2019. Using patterns to capture and transfer tacit knowledge in virtual project teams. *The Journal of Modern Project Management*, 7(2).
- Sauer, P.C. and Seuring, S., 2023. How to conduct systematic literature reviews in management research: a guide in 6 steps and 14 decisions. *Review of Managerial Science*, 17(5), pp.1899-1933.
- Serenko, A., 2022. The great resignation: the great knowledge exodus or the onset of the great knowledge revolution?. *Journal of Knowledge Management*, 27(4), pp.1042-1055.
- Shepherd, A. and Cooper, J., 2020. Knowledge management for virtual teams. *Issues in Information Systems*, 21(1), pp.62-68.
- Staples, D.S. and Webster, J., 2008. Exploring the effects of trust, task interdependence and virtualness on knowledge sharing in teams. *Information systems journal*, 18(6), pp.617-640.
- Tietz, S. and Werner, K., 2022. Influencing factors on knowledge sharing in virtual teams. *Work*, 72(4), pp.1745-1763.
- Tranfield, D., Denyer, D. and Smart, P., 2003. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), pp.207-222.
- Wende, E. and King, G., 2015, January. Exploring storytelling for relationship building in offshore outsourced projects: An action research investigation. In *2015 48th Hawaii International Conference on System Sciences* (pp. 412-421). IEEE.

Willson, R., Dalkir, K. and Montazeri, P., 2024. What Is Left Unsaid: Ongoing Tacit Knowledge Loss from the Pandemic. *Proceedings of the Association for Information Science and Technology*, 61(1), pp.1138-1140.

TEAM LEARNING BEHAVIOURS LEADING TO TEAM SHARED MENTAL MODELS, A CASE STUDY

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Keywords: Team learning, team shared mental models.

The organization is a system that incorporates the organization, the team, and the individual, the three of them consisting its boundaries. The system structure and the rules of interaction (the decision rules in the system), indicate the patterns of behavior within the system. This research adopts a system thinking to comprehend the nature of interdependencies along individual parts and agents. We assume that the team system consists of a number of heterogeneous agents, and each of those agents makes decisions about how to behave, learn and interact with one another. To gain insight in the social processes which team learning behaviors lead to the construction of a shared mental model, this research explores how the development of shared mental models correlates with team learning behaviors.

A mental model is a representation of reality we construct in our brain (Senge, 1990). Gaining an understanding of how teams may navigate and make optimal decisions in dynamic complex environments constitutes one of the main challenges for team researchers in the coming years. Senge's *The Fifth Discipline* (Senge, 1990) reinforce the idea of the organization as a learning system. Understanding the cognitive structures and processes of teams is essential in comprehending team task execution, as well as predicting and explaining team performance, due to the cognitive and information-intensive nature of project team tasks (Hinsz et al, 1997) . According to DeChurch (DeChurch, 2010) and Mesmer-Magnus, meta-analytic findings, there is a robust association between team cognitive structures, team processes, and team performance.

The literature on team cognition emphasizes the significance of mental models, which are identifies as structured representations that team members possess of the elements of their task or team environment (Mohammed, 2010). Shared Mental Models (SMMs) occur in teams whose members have similar mental models of their task and of the team itself. Shared mental models (SMMs) are an extension of mental model theory, proposed by Converse, Salas, and Cannon-Bowers as a paradigm to study team training (Converse et al.,1993). Mental models are simplified system descriptions, employed by humans when systems, particularly modern socio-technical systems, are too complex for humans to understand in full detail. Within the learning sciences only few studies have tried to directly measure shared mental models (e.g., Jeong and Chi 2007; Fischer and Mandl 2005). Team learning behaviors are related to the development of a shared mental model, however, the relation appears to be complex.

To determine the patterns that can be considered as team learning behavior, we use of the concepts of construction, co-construction and constructive conflict, building on research in the learning sciences (e.g., Dillenbourg et al. 1996; Alpay et al. 1998; Dillenbourg and Traum 2006) and branches of linguistic research on models

of conversation, discourse and dialogue (Baker 1995; Edmondson 1981). These two disciplines provide a framework on interactions constituting team learning (Dillenbourg et al., 1996) and note that achieving a shared mental model presupposes joint understanding (Baker 1995). It is, however, not only a matter of understanding each other's representation (mutual understanding), but also of accepting and incorporating each other's ways of seeing (mutual agreement) (Dillenbourg and Traum 2006). In reaching mutual understanding and agreement, the following processes are crucial. First, meaning or understanding needs to be (co-)constructed. This is not done through simple accumulation of the contributions of individuals, because these contributions 'build on' previous ones. Second, agreement needs to be established about the proposed solution (Baker 1995). The role of conflict, as the process resulting from differences in point of view, is highly relevant here (De Dreu and Weingart 2003). Previous research confirmed the value of these socio-cognitive processes in understanding team learning behavior in collaborative learning environments (Van den Bossche et al. 2006).

The research methodology used 176 first-year bachelor students in an Business degree program, that participated in the research for extra credit. The participants were divided into random teams and had to fulfil three team activities. The results indicate that a team learning perspective provides insight in how people share knowledge. Particularly the team learning behaviors identified as co-construction and constructive conflict are related to the development of shared mental models. In addition, a shared mental model of the task environment in a team leads to improved performance. This underscores the importance of developing shared cognition in teamwork. Constructive conflict seems to be a significant behavior in the process of building shared mental model. On the other hand, the team behaviors conceptualized as co-construction do not in themselves contribute to the development of shared mental models.

References

- Baker, M. (1995) Corpora in Translation Studies: An Overview and Suggestions for Future Research. *Target*, 7, 223- 242. <http://dx.doi.org/10.1075/target.7.2.03bak>
- Cannon-Bowers, J. A., Salas, E., & Converse, S. (1993). Shared mental models in expert team decision making. In N. J. Castellan, Jr. (Ed.), *Individual and group decision making: Current issues* (pp. 221-246). Lawrence Erlbaum Associates, Inc.
- De Dreu, C. K. W., & Weingart, L. R. (2003). Task versus relationship conflict, team performance, and team member satisfaction: A meta-analysis. *Journal of Applied Psychology*, 88(4), 741-749. <https://doi.org/10.1037/0021-9010.88.4.741>
- DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). The cognitive underpinnings of effective teamwork: A meta-analysis. *Journal of Applied Psychology*, 95(1), 32-53. <https://doi.org/10.1037/a0017328>
- Dillenbourg, Pierre & Baker, Michael & Blaye, Agnes & O'Malley, Claire. (1996). The evolution of research on collaborative learning. The evolution of research on collaborative learning. In E. Spada & P. Reiman (Eds) *Learning in Humans and Machine: Towards an interdisciplinary learning science*. (Pp. 189- 211). Oxford: Elsevier.
- Dillenbourg, Pierre & Traum, David. (2006). *Sharing Solutions: Persistence and*

Grounding in Multimodal Collaborative Problem Solving. *Journal of the Learning Sciences*. 15, 121-151.

Edmondson, A. C. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly*, 44(2), 350–383.

Edmondson, A. C. (2019). *The fearless organization: Creating psychological safety in the workplace for learning, innovation, and growth*. Wiley.

Fischer, F., & Mandl, H. (2005). Knowledge Convergence in Computer-Supported Collaborative Learning: The Role of External Representation Tools. *Journal of the Learning Sciences*, 14(3), 405–441.

Hinsz, V. B., Tindale, R. S., & Vollrath, D. A. (1997). The emerging conceptualization of groups as information processors. *Psychological Bulletin*, 121(1), 43–64.

Jeong, H., & Chi, M. T. H. (2007). Knowledge convergence and collaborative learning. *Instructional Science*, 35, 287-315.

Mohammed, U. (2010) A Six Step Block Method for Solution of Fourth Order Ordinary Differential Equations. *The Pacific Journal of Science and Technology*, 11, 258-265

Senge, P. (1990). *The Fifth Discipline: The Art and Practice of the Learning Organization*. New York: Doubleday/Currency.

Van den Bossche, Piet & R.Segers, Mien & Kirschner, Paul. (2006). Social and cognitive factors driving teamwork in collaborative learning environments : Team learning beliefs and behaviors. *Small Group Research*. 37 (5).

Session B3

BLOCKCHAIN FRONTIERS

**Chair: Christina Tarnaridou, Athens University of Economics and
Business, Greece**

GOVERNANCE IN THE AGE OF GENERATIVITY: RECONCILING DISTRIBUTED LEDGER TECHNOLOGIES AND GENERATIVE ALGORITHMIC SOLUTIONS

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Keywords: Distributed Ledger Technologies (DLT), blockchain, Generative Algorithmic Solutions (GAS), generative AI, digital governance.

In this study, we examine the interplay between Distributed Ledger Technologies (DLT) and Generative Algorithmic Solutions (GAS) by distinguishing between the governance of technology—where institutions regulate algorithmic processes—and governance by technology—where autonomous systems enforce rules. Our aim is to reconcile these two perspectives by understanding how they interact and where tensions emerge. Drawing upon the affordance theory perspective (Leonardi, 2011) and polycentric governance theory (Ostrom, 2009), we clarify the mechanisms that arise from the intersectionality of DLT and GAS. Using a meta-synthesis approach (Jeyaraj et al., 2020), we highlight inherent tensions and propose conceptual advancements that refine models combining DLT and GAS, reconciling the meaning and operational dynamics of these intertwined governance paradigms.

Contemporary digital technologies demand novel agile governance, while traditional, centralized control is rapidly yielding to systems that blur the lines between human agency and algorithmic decision-making (Hanisch et al., 2023; Constantinides & Barrett, 2015; Henfridsson & Bygstad, 2013). We refer to governance as the institutional and procedural mechanisms that guide decision-making, which must evolve to accommodate increasingly decentralized and autonomous environments (Tiwana, 2013; Ossewaarde et al., 2017). In doing so, we examine two technological paradigms that lie at the epicenter of this shift: DLT and GAS. DLT provides immutable records, decentralization, and cryptographic security. In contrast, GAS—defined here as unsupervised and semi-supervised machine learning algorithms trained on multimodal content to generate new outputs when prompted—brings enhanced autonomy, recognition capabilities, and adaptability (Carlson, 2019, Zhang et al., 2021). The intersectionality of these digital technologies is reshaping industries and challenging established notions of trust, accountability, and regulation (Kumar et al., 2023).

The integration of GAS and DLT is fostering innovative, data-driven business models that demand updated regulatory frameworks addressing data ownership, storage, and transfer (Berg et al., 2023; Hanisch et al., 2023). As authority shifts from centralized institutions to decentralized, algorithm-driven systems, traditional governance models must evolve. DLT ensures data provenance and auditability, while GAS enhances smart contract functionality and automates dispute resolution (England et al., 2021; Bhumichai et al., 2024). Together, these technologies afford more streamlined operations across finance, supply chains, and content authentication, but they also introduce significant challenges (Akrami et al., 2023).

Despite the decentralized nature of DLT, the development and optimization of

GAS remains concentrated among a few dominant firms (Kumar, 2024). Tokenized ecosystems, which are intended to democratize algorithmic training, risk deepening market imbalances (Heines et al., 2021). Moreover, the convergence of GAS and DLT raises tensions that necessitate a refined framework. For instance, GAS systems generate new content by synthesizing vast amounts of multimodal data, thereby complicating issues of intellectual property and creative ownership. Current frameworks, which assume a clear human creator, struggle to assign accountability when an algorithm produces novel work (Fenwick & Jurcys, 2023; Makridis et al., 2024). Immutable DLT records further complicate retroactive changes, as evidenced by challenges in decentralized smart contracts (Zhang et al., 2021). This scenario highlights the need for flexible frameworks that bridge the rigidity of DLT with the probabilistic nature of GAS.

The union of GAS with DLT can also hinder the development of new economic models, such as tokenized ecosystems and nonfungible tokens (NFTs), which have the potential to democratize creative ownership. However, if control over GAS remains concentrated, these models may exacerbate market imbalances (Kumar, 2024). Establishing fair incentive structures is essential to ensure decentralized participation and a balanced distribution of rewards between human and algorithmic contributions. Finally, merging GAS and DLT poses technical implications (Vubangsi et al., 2021). Variations among GAS frameworks and DLT platforms, along with scalability issues, highlight the need for robust interoperability standards. These standards are critical for integrating the adaptive capabilities of GAS with the immutable recordkeeping of DLT, thereby maintaining governance frameworks that are both dynamic and verifiable.

A crucial distinction in our study is between the governance of technology and governance by technology. Traditionally, governance has been top-down, with institutions regulating technological operations. Governance of technology refers to how institutions manage the predictive decision-making of GAS and the automated enforcement of DLT (Tiwana, 2013). For instance, governments can impose legal frameworks to address issues such as data transparency, DLT-based financial instruments, and decentralized applications (Bhumichai et al., 2024). The EU AI Act, for example, requires high-risk GAS models to explain their outputs, yet retroactive modifications become challenging when these models are embedded in immutable smart contracts (Zhang et al., 2021). Similarly, DLT-based healthcare systems must balance transparency and privacy under GDPR and HIPAA while preserving data integrity (England et al., 2021), making the use of GAS in this setting particularly fragile, despite the immense promise it can bring for the quality and speed of healthcare delivery.

In contrast, governance by technology implies that DLT and GAS themselves act as autonomous enforcers. DLT-based smart contracts execute transactions and manage workflows without human intervention. In finance, GAS-driven compliance tools adjust risk parameters and interest rates in real time, managing risk in ways that extend beyond traditional regulatory frameworks (Bhumichai et al., 2024). In supply chains, GAS-powered logistics systems autonomously manage shipments while DLT ensures tamper-proof product provenance (Vubangsi et al., 2024). Reconciling these two perspectives requires an understanding that while institutions continue to

shape and oversee the operation of GAS and DLT, these technologies also embody self-regulatory mechanisms that operate independently (Kalenzi, 2022).

Such a duality extends to areas such as content verification, media provenance, and copyright protection. GAS-powered deepfake detection systems integrated with DLT-based authentication platforms enhance content integrity and combat misinformation (Berg et al., 2023; Vubangsi et al., 2024). Moreover, DLT-based copyright registries could enforce ownership of GAS-generated content, enabling smart contracts to distribute royalties and reduce legal disputes (Bhumichai et al., 2024). Nonetheless, concerns persist regarding the legitimacy of GAS-authored content, the potential for GAS bias, and the challenges of cross-jurisdictional enforcement (Fenwick & Jurcys, 2023).

Self-sovereign identity (SSI) frameworks further illustrate the convergence between these governance models. GAS-enhanced fraud detection in decentralized identity systems enables rigorous verification, while DLT guarantees tamper-proof records (England et al., 2021). Pilot programs in KYC (Know Your Customer) and AML (Anti-Money Laundering) have successfully used GAS to flag suspicious transactions and DLT to secure immutable audit trails (Bhumichai et al., 2024). Yet, reliance on behavioral data may reinforce biases, potentially leading to automated exclusion or racial profiling (Zhang et al., 2021).

A notable tension arises between DLT's determinism and GAS's probabilistic nature (Berg et al., 2023). While DLT enforces an immutable record of decisions, it lacks the flexibility to correct errors generated by GAS. This paradox underscores the need for adaptive structures that allow real-time auditing without undermining the distinct benefits of each technology (Fenwick & Jurcys, 2023).

In response to these challenges, our study offers a conceptual framework that bridges the governance of technology—where institutions regulate DLT and GAS—and governance by technology—where these digital technologies autonomously enforce rules. By synthesizing insights from affordance theory and polycentric governance, we bring forward the key tensions and propose pathways for reconciling the deterministic nature of DLT with the probabilistic adaptability of GAS. The findings of our work contribute to refining governance models that balance institutional oversight with algorithmic autonomy, ensuring both regulatory compliance and technological innovation. Our study thus provides a structured approach to understanding and navigating the complex interplay between these emerging paradigms, offering theoretical advancements and practical considerations for policymakers, industry leaders, and researchers.

References

- Akrami, N. E., Hanine, M., Flores, E. S., Aray, D. G., & Ashraf, I. (2023). Unleashing the Potential of Blockchain and Machine Learning: Insights and Emerging Trends From Bibliometric Analysis. *IEEE Access*, 11, 78879-78903. <https://doi.org/10.1109/access.2023.3298371>
- Berg, C., Davidson, S., & Potts, J. (2023). Institutions to constrain chaotic robots: Why generative AI needs blockchain. Available at SSRN.
- Bhumichai, D., Smiliotopoulos, C., Benton, R., Kambourakis, G., & Damopoulos, D. (2024). The Convergence of Artificial Intelligence and Blockchain: The

State of Play and the Road Ahead. *Information*, 15(5). <https://doi.org/10.3390/info15050268>

Brewer, J., Patel, D., Kim, D., & Murray, A. (2024). Navigating the challenges of generative technologies: Proposing the integration of artificial intelligence and blockchain. *Business Horizons*, 67(5), 525-535. <https://doi.org/10.1016/j.bushor.2024.04.011>

Carlson, K. W. (2019). Safe Artificial General Intelligence via Distributed Ledger Technology. *Big Data and Cognitive Computing*, 3(3). <https://doi.org/10.3390/bdcc3030040>

Constantinides, P., & Barrett, M. (2015). Information Infrastructure Development and Governance as Collective Action. *Information Systems Research*, 26(1), 40-56. <https://doi.org/10.1287/isre.2014.0542>

England, P., Malvar, H. S., Horvitz, E., Stokes, J. W., Fournet, C., Burke-Aguero, R., ... & Zaman, A. (2021, July). Amp: Authentication of media via provenance. In *Proceedings of the 12th ACM Multimedia Systems Conference* (pp. 108-121).

Fenwick, M., & Jurcys, P. (2023). Originality and the future of copyright in an age of generative AI. *Computer Law & Security Review*, 51, 105892. <https://doi.org/10.1016/j.clsr.2023.105892>

Hanisch, M., Goldsby, C. M., Fabian, N. E., & Oehmichen, J. (2023). Digital governance: A conceptual framework and research agenda. *Journal of Business Research*, 162. <https://doi.org/10.1016/j.jbusres.2023.113777>

Heines, Roger; Dick, Christian; Pohle, Christian; and Jung, Reinhard, "The Tokenization of Everything: Towards a Framework for Understanding the Potentials of Tokenized Assets" (2021). *PACIS 2021 Proceedings*. 40. <https://aisel.aisnet.org/pacis2021/40>

Henfridsson, Ola, and Bendik Bygstad. "The generative mechanisms of digital infrastructure evolution." *MIS quarterly* (2013): 907-931.

Jeyaraj, A., & Dwivedi, Y. K. (2020). Meta-analysis in information systems research: Review and recommendations. *International Journal of Information Management*, 55, 102226. <https://doi.org/10.1016/j.ijinfomgt.2020.102226>

Kalenzi, C. (2022). Artificial Intelligence and Blockchain: How Should Emerging Technologies Be Governed? *Front Res Metr Anal*, 7, 801549. <https://doi.org/10.3389/frma.2022.801549>

Kumar, S., Lim, W. M., Sivarajah, U., & Kaur, J. (2023). Artificial Intelligence and Blockchain Integration in Business: Trends from a Bibliometric-Content Analysis. *Information Systems Frontiers*, 25(2), 871-896. <https://doi.org/10.1007/s10796-022-10279-0>

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS quarterly*, 147-167.

Nguyen, C.T., Liu, Y., Du, H., Hoang, D.T., Niyato, D., Nguyen, D.N., Mao, S., 2024. Generative AI-enabled Blockchain Networks: Fundamentals, Applications, and Case Study. *IEEE Network* 1-1.. <https://doi.org/10.1109/mnet.2024.3412161>

Nguyen Thanh, B., Son, H. X., & Vo, D. T. H. (2024). Blockchain: The Economic and Financial Institution for Autonomous AI? *Journal of Risk and Financial*

Management, 17(2). <https://doi.org/10.3390/jrfm17020054>

Ostrom, E. (2009). Understanding institutional diversity. Princeton university press.

Ossewaarde, M., & Reijers, W. (2017). The illusion of the digital commons: 'False consciousness' in online alternative economies. *Organization*, 24(5), 609-628. <https://doi.org/10.1177/1350508417713217>

Tiwana, A. (2013). Platform Ecosystems: Aligning Architecture, Governance, and Strategy.

Vubangsi, M., Nyuga, G., & Al-Turjman, F. (2024). Exploring the Intersection of Artificial Intelligence and Blockchain Technology in Complex Systems: A Systematic Review. In (pp. 235-245). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-63103-0_25

Zhang, Z., Song, X., Liu, L., Yin, J., Wang, Y., Lan, D., & Kumar, N. (2021). Recent Advances in Blockchain and Artificial Intelligence Integration: Feasibility Analysis, Research Issues, Applications, Challenges, and Future Work. *Security and Communication Networks*, 2021, 1-15. <https://doi.org/10.1155/2021/9991535>

BREAKING THE CHAIN: UNLOCKING THE POTENTIAL OF DISTRIBUTED LEDGER TECHNOLOGY FOR THE PUBLIC SECTOR

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Keywords: Distributed ledger technology, blockchain, public sector organisations, digital governance.

Extended Abstract

Public sector organizations around the world increasingly embrace digital technologies to streamline operations and provide a more citizen centric model of public governance to better serve the needs of citizens (Twizeyimana and Andersson, 2019). However, the conservative nature of public sector organizations along with their need for increased security, accountability and compliance, presents challenges in adopting novel digital technological. For instance, while distributed ledger technology (DLT) promises enhanced transparency and trust in government services (Beck et al., 2018), its adoption remains limited (Kassen, 2022), with most initiatives either stalling at pilot stage or being abandoned. Unlike other digital technologies that can be implemented in stages and can be adopted incrementally by organizations, DLT requires fundamental restructuring of existing processes and trust mechanisms.

Our work seeks to identify public sector areas where DLT can have the greatest impact, as well as to explore the trade-offs and limitations associated with its adoption. Through a qualitative methodological approach combining semi-structured interviews with expert informants as well as archival analysis of available secondary data, we identify several critical challenges and success factors in DLT implementation. Our findings unearth significant barriers including i) political reluctance stemming from the historical association of DLT with fraudulent activities, ii) regulatory ambiguities across borders, iii) privacy concerns, iv) interoperability deficits, and v) absence of a widely recognized 'killer application'.

Specifically, we conducted interviews with a diverse range of stakeholders involved in DLT initiatives in the public sector, including experts from relevant international associations, and representatives from ministries across Europe. In doing so, we collected insights from a wide array of stakeholders—public sector officials, technology providers, and industry experts—resulting in a comprehensive understanding of the challenges, opportunities, and practical considerations of applying DLT in the public sector. From these interviews, several key themes emerged. Among the challenges discussed by the experts were concerns about reputation risks, data privacy, regulatory barriers, and the lack of meaningful use cases. In terms of benefits, DLT was seen as a way to increase transparency and improve trust in governmental processes. The interviews highlighted the importance of identifying meaningful applications for DLT and emphasized that successful projects depend on clear governance frameworks.

To systematically categorize and evaluate DLT initiatives, we develop a comprehensive taxonomy (Nickerson et al., 2013), which incorporates four meta-characteristics: i) domain of application, ii) geographical region, iii) project status, and iv) orga-

nizational type. Our taxonomy is based on a secondary data analysis focusing on DLT applications in the public sector globally. Together, these meta-characteristics provide a structured way to assess DLT projects in the public sector, enabling the identification of patterns, challenges, and opportunities across various regions, domains, and types of organizations. Our taxonomy also offers insights into the maturity of DLT applications by tracking the status of projects, contributing to a better understanding of the role of DLT in government functions.

Our preliminary findings reveal distinct regional trends. For instance, in developing economies, DLT initiatives predominantly focus on Central Bank Digital Currencies, demonstrating its potential to democratize financial systems and overcome infrastructural limitations. Conversely, developed regions prioritize digital identity management applications, reflecting different institutional priorities and technological maturity levels. These findings highlight the adaptability of DLT across socioeconomic contexts and underscore the importance of governance structures in shaping implementation strategies.

Our work advances both theoretical understanding and practical implementation of DLT in public sector contexts. The primary contribution we bring forward is the development of a comprehensive methodological framework that bridges the gap between the decentralized architecture of DLT and the centralized nature of government operations. This novel framework encompasses both technical implementation guidelines and governance adaptation strategies, providing public sector organizations with actionable approaches for blockchain adoption while preserving institutional integrity. Our methodological approach specifically addresses the unique challenges faced by government institutions, including regulatory compliance, accountability requirements, and the need for systematic change management. By incorporating insights from successful implementations across various regions, we provide empirically-validated strategies for maintaining the fundamental benefits of DLT for transparency and decentralization within traditionally centralized structures. Our framework particularly emphasizes the critical balance between innovation and institutional stability, offering specific guidance for adapting existing governance mechanisms to accommodate blockchain-based systems. Furthermore, our work introduces a structured approach for resolving the inherent tension between centralized authority and decentralized technology. Our approach encompasses both technical architecture considerations and organizational change management strategies, providing public sector leaders with a comprehensive roadmap for blockchain implementation. The adaptability of our framework across governmental contexts ensures its relevance for various public sector organizations, from municipal authorities to national institutions, while maintaining the rigor necessary for government operations.

References

- Beck, R., Müller-Bloch, C., King, J.L., 2018. Governance in the blockchain economy: A framework and research agenda. *J. Assoc. Inf. Syst.* 19, 1.
- Kassen, M., 2022. Blockchain and e-government innovation: Automation of public information processes. *Inf. Syst.* 103, 101862. <https://doi.org/10.1016/j.is.2021.101862>
- Nickerson, R.C., Varshney, U., Muntermann, J., 2013. A method for taxonomy

development and its application in information systems. *Eur. J. Inf. Syst.* 22, 336–359. <https://doi.org/10.1057/ejis.2012.26>

Twizeyimana, J.D., Andersson, A., 2019. The public value of E-Government—A literature review. *Gov. Inf. Q.* 36, 167–178.

TRADING & POST-TRADING OPERATIONS AS AN AFTERMATH OF THE BLOCKCHAIN PROCESS

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Keywords: Execution, clearing, financial instruments, post-trading, blockchain, DLT, financial markets, supervision.

Scope of the analysis

The analysis refers to financial markets where trading in financial instruments takes place. It points out the impact of digital technology, named as blockchain or even DLT (distributed ledger technology), on said markets. In particular, the analysis focuses on the implementation of this new technology rules in the environment of "electronic securities", "derivatives" and other "complex assets" transactions. The DLT concepts in financial markets have already been regulated in Greece under Law 5113/2024. This piece of legislation is a matter of adaptation to the provisions of Regulation (EU)2022/858, the so-called Distributed Ledger Technology Regulation (or DLTR). These new aspects of regulations are of utmost importance for financing and investments in Europe.

In reviewing the concepts, the following indicative examples are crucial in terms of understanding the potential scope of new technology. The examples refer to the product of shares of a public limited company. In this example, the company issues shares as part of a share capital increase. Through the issuance, the company raises new investment funds to enhance its operations and activities. In this case, it is obvious that the shares issued become a means of financing of the company. As a complement to this example, the second one refers to shares issued under the request to be admitted to trading on a market, such as an exchange. In this case, the shares issued under the regime of listed shares become financial instruments enabling the formation of a wide variety of secondary products and markets. More specifically, in addition to spot transactions (e.g. buying and selling shares), the relevant investments may vary as complex transactions (forward, options, futures and others) that operate under more sophisticated parameters, referring to various markets (e.g. equity markets or bond markets) and relevant investment parameters (e.g. physically-settled or cash-settled contracts). All the above fall into the scope of financial instruments as referred to in EU regulations already incorporated into the Greek reality (Law 4514/2018).

The above transactions are examined under this work from the parameter of their execution, clearing and settlement based on blockchain technology.

Blockchain and functional approach

Blockchain, as a new method of building markets, has a catalytic effect on their structure and operations. It supports market operations without intermediaries and participants, or even without financial market infrastructures mainly referring to clearing houses or central counterparties and financial institutions, such as custodians, by creating a new transacting structure being based directly on the investors' portfolios or "wallets".

In this context, the investor is permitted to maintain more autonomously his investment account in DLT, without being dependent on the ancillary services of a "back office" (e.g. safekeeping, portfolio management, balance reconciliations, etc.) of banks or other investment firms. This also impacts the settlement cycle of the transactions that can operate under the T+0 rule instead of the traditional T+2 rule.

Notable is that initiatives have already been taken in Europe to switch from "T+2" to "T+1" as a first reaction to the automation steps of new technology adopted in USA. Under the above modern approach transactions can be concluded and settled at the same time, simultaneously, due to the new blockchain infrastructure concepts where execution and settlement takes place in tokens (DLTR pt.3 preamble). This relates to the fact that the digital representation of financial instruments on distributed ledgers allows them to be issued, stored and transferred on a distributed ledger in tokens. DLT and tokens definition becomes the new reality in the regulatory and real financial world (Greek Law 5113/2024 (article 3 (a))).

Legal and supervisory parametrisations

The new DLT texture of the operation of infrastructures (e.g. stock exchange, clearing houses, etc.) and the related services provided by intermediaries (order executing, trading, custody, etc.) signals changes both in their legal nature and the supervisory approach. The service ceases to operate under the hard-coded intermediation. It is, or can be, the "disintermediation" service with different consequences for the operation of transactions and investments.

This legal shift inevitably raises supervisory concerns on whether the new structure covers the risks and, in general, the legal policy objectives that the traditional model of financial markets is called upon to serve. Under the raised supervisory concerns if, as a consequence of the application of the new technology, transactions carried out in a market are settled as above at T+0 time, it is reasonable to question whether the clearing function, performed by advanced systems and entities, in particular the so-called central counterparties-CCPs (Regulation (EU) 648/2012 - EMIR), has a *raison d'être* or becomes redundant. The above consideration stems from the fact that clearing and risk management in a market aim at covering the counterparty risk that due to the application of T+0 rule will no longer exist.

Further to the above supervisory concerns, a number of issues are raised due to the application of the new technology on trading markets and execution venues. Indicatively, if participation in a blockchain market under the disintermediation conditions does indeed require the directly participating investors to be fully prepared to fulfil their trading obligations (T+0), it is reasonable to ask whether such participation can be feasible in practice given that investors are not necessarily professionals and hence not in a position to have the readiness to meet market requirements. Put it differently, there is a case of how retail investors may continue to operate their investments. The new reality may contravene to market constraints attributable to more sophisticated trading, such as algo-trading which by definition presupposes investors as users to have a more professional profile (art.21, Regulation (EU) 2017/584, art.22 Regulation (EU) 2017/589, art. 1.4.5 Athens Exchange Regulation, no. 19/697/10-11-2014 HCMC Decision GGB/3195/27.11.2014, as in

force).

Other related concerns refer to the main model of financial markets and the investors protection (art.27, Law 4514/2018, Regulation (EU) 600/2014, MiFIR). If, therefore, the new technology introduces requirements for participation in the markets with "T+0" execution, which investors, especially of the size of private ones, cannot meet, it can reasonably be argued that the users of the technology and the new market structure introduced will not be the investors themselves, under the design of the "permissionless systems", but only those who will have the guarantees to respond. Therefore, the transaction from "wallet to wallet", requiring a higher degree of readiness for automatic execution and settlement, is questionable if can be implemented as an investor-to-investor transaction (peer-to-peer). But if this is the case, it could be difficult to support that apart from professionals there will be room for retail investors to transact directly from wallet to wallet through the digital financial markets.

Context of the paper

The paper addresses these issues under:

- Part I entitled "Preliminary observations: Markets and new digital technology", where the scope of the analysis and the main legal and supervisory observations are defined;
- Part II entitled "The chronicle of post-trading operations in the financial sector", where a historical review is made of the institutions of the relevant transactions from the perspective of both execution and clearing, as formed under the relevant legislative route at a national and EU level (Greek Laws 3632/1928, 2471/1997, 2533/1997, 3606/2007, EMIR);
- Part III entitled "The new digital securities approaches" where the main legal reflections of Greek Law 5113/2024 are captured with regard to blockchain, DLT and tokenisation; and
- Part IV entitled "Digital Directions in Financial Instruments: Towards a New Regulatory Reform", where legal concerns related to the new landscape are discussed.

The paper includes the below indicative references.

References

Greek bibliography (indicative)

Avgitidis D., Capital Markets Law, Nomiki Bibliothiki Publications, 2nd ed., 2019

Avgitidis D., The commercial capacity of the investor of a stock exchange transaction, ComLawRev/EEmpD 1998, 241

Vervesos N., The principle of equal treatment in Capital Markets Law (2016)

Karagounidis Ap., The obligation of credit institutions and investment firms (EPEY) to execute orders on terms most favorable to the client (best execution), ComLawRev/EpiskED, 2009, 231

Lekkas G., Financial collateral arrangements on financial instruments and credit claims and good faith, in commemor. Vol. Georgakopoulos, 2016, 451 et seq.

Liakopoulos Th., Commercial Law Issues II – Commercial Contracts – General

Part (1997)

Rigas K., The course of the Greek capital market from dematerialization to digitalization through ATHEXCSD Rulebook, focusing on the legal nature, transfer, encumbrance and forced sale of capital market securities, Greek Justice 2 (2023), 345

Sotiropoulos G., Securities lending (2005)

Tarnanidou Chr., Book-Entry Securities Law (2021)

Tarnanidou Chr., Developments in capital markets supervision: On the occasion of the example of adaptation to the European Regulation No 648/2012 ('European Market Infrastructure Regulation' – EMIR") in State, Economy and Enterprise – 24th Panhellenic Conference on Commercial Law (2015), 505

Tarnanidou Chr., Omnibus Accounts and their implications to company law, Commercial Companies Law/DEE 2018/12, 1386

Tarnanidou Chr., Derivative Contracts of the Financial Sector (2006)

Tountopoulos V., Capital Markets Law (2023)

Triantafyllakis G., The protection of the investor as consumer from market abuse (manipulation), Commercial Companies Law/DEE 2008, 521

Tsibanoulis D., Clearing of financial transactions in The Stock Exchange in Greek Law, 9th Panhellenic Conference on Commercial Law (2000), 265

Tsibanoulis D., Investment services in Greek and Community law mainly relating to stock exchange transactions (1989)

Foreign bibliography – EU and other papers and reports (indicative)

Armstrong Dean QC – Hyde Dan – Thomas Sam, Blockchain and Cryptocurrency: International Legal and Regulatory Challenges (2019)

Baker Collen – Werbach Kevin, Blockchain in Financial Services in Fintech Law and regulation (Madir J.) (2019), 123

Bank for International Settlements - International Organization of Securities Commissions, Principles for financial market infrastructures (2012) [BIS-IOSCO]

Burn Lachlan, Regulatory Framework in Europe in European Securities Law (2021), 4

ESMA, Opinion- Common indicators for new products and services under Article 15 and for significant changes under Article 49 of EMIR (Date: 15 November 2016 Ref.: ESMA/2016/1574)

European Association of CCP Clearing Houses, Decentralized Clearing? An Assessment of the impact of DLTs on CCPs - EACH Forum paper (Feb.2023) [EACH]

European T+1 Industry Task Force, High-Level Roadmap in EU Securities Markets (Oct.2024) [European T+1 Industry Task Force]

Financial Markets Law Committee (FMLC), Distributed Ledger Technology and Governing Law: Issues of Legal Uncertainty (March 2018)

Glossary of Key Terms, in Fintech Law and regulation (Madir J.) (2019), xxvii
LabCFTC, A Primer on Smart Contracts (Nov 27, 2018) [CFTC]

Madir Jelena, Introduction – What is in FinTech? in FinTech Law and Regulation (Madir J.) (2019), 1

Niamh Moloney, EU Securities and Financial Markets Regulation (2014)

Paech Ph., Market needs as paradigm: breaking up the thinking on EU securities law in Intermediated Securities in The Impact of Geneva Securities Convention and

- the Future European Legislation (P.H. Conac, Ul. Segna, L. Thevenoz) (2013), 22
- Stabile Daniel T., Prior Kimberly A., Hinkes Andrew M., Digital Assets and Blockchain Technology. US Law and Regulations (2020)
- Tarnanidou, From the Home Member State Principle to EMIR, ESMA and the Colleges, Financial Regulation International, March 2015, Issue 18.2, 13-20
- Territt Harriet, Governing the Blockchain: What is the Applicable Law in Fintech Law and regulation (Madir J.) (2019), 171
- Thevenoz L., Intermediated Securities, Legal Risk and the International Harmonization of Commercial Law (2007) (http://works.bepress.com/luc_thevenoz/1), 1-69
- Wendehorst Ch., Proprietary Rights in Digital Assets and the Conflict of Laws in Blockchain and Private International Law (Brill — Nijhoff) (2023) 101-127
- Yates Madeleine, International Settlement in International Securities Markets and Clearing System in Financial Markets and Exchanges Law (2007), 501
- Zetsche Dirk A. / Buckley Ross P. / Arner Douglas W., Liability of Distributed Ledgers: Legal Risks of Blockchain, EBI Working Paper Series 2017 no 14, 42
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Session C3

RETHINKING HIGHER EDUCATION FOR THE AI ERA

Chair: Nancy Pouloudi, Athens University of Economics and Business,
Greece

THE AI REVOLUTION IN BUSINESS EDUCATION: FROM ONE-SIZE-FITS-ALL TO HYPER-PERSONALIZED LEARNING

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Keywords: Personalized learning, AI integration, business education, curriculum innovation.

Abstract

This session will discuss how artificial intelligence is fundamentally transforming business education by creating truly personalized learning experiences that adapt in real-time to each student's needs, pace, and career goals. This session will reveal breakthrough strategies for integrating AI to revolutionize curriculum delivery, enhance pedagogical approaches, and create individualized pathways that prepare graduates for an AI-dominated business landscape. We will share a strategic framework, navigate implementation challenges, and showcase early results that are reshaping the future of business education. Attendees will walk away with actionable insights and a roadmap for leveraging AI to boost academic relevance, enhance student engagement, and amplify institutional impact in the AI age.

BEYOND OPTIMISATION: RETHINKING AI-DRIVEN ALGORITHMS ON SOCIAL MEDIA FOR HUMAN FLOURISHING

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Keywords: Social media, AI-driven algorithm, engagement, online community, trust.

Artificial intelligence (AI) plays a defining role in shaping information consumption, particularly on social media platforms. This raises urgent questions for business education and research: How should AI-driven platforms be designed and managed to serve society's long-term interests? Current algorithms prioritize optimization for ad revenue, maximizing clicks, views, and watch time. However, this single-minded focus often comes at the expense of social cohesion and trust.

YouTube's recommendation system is a prime example, as it significantly influences content exposure. While effective for retention, its engagement-driven design fosters algorithmic bias, prioritizing interaction over balanced information. This leads to filter bubbles and echo chambers, reinforcing users' existing views and fueling political polarization. Many critiques frame users as passive consumers, vulnerable to algorithmic manipulation, with little agency to resist.

This presentation examines YouTube's recommendation bias through the case study of *Ethnic Neighbourhoods*, a documentary series exploring culturally diverse communities. Drawing on AI ethics, platform design, digital trust, and media sociology, we analyze how algorithmic engagement loops can reinforce polarization but also cultivate resilience and deeper insight among audiences. By evaluating these paradoxical effects, we identify what is missing in current platform design and propose strategies to steer AI towards ethical, trust-centered, designed for human flourishing.

AI Algorithms, Social Media, and Polarisation

AI-driven recommendation systems on platforms like YouTube and Instagram prioritize engagement as their primary metric of success. By design, these algorithms continuously serve users content most likely to capture their attention, optimizing for ad revenue and watch time. Scholars argue that this business model promotes "polarization for profit", as algorithms amplify content that triggers fear, outrage, or indignation, increasing interaction rates. Research highlights that emotionally charged or extreme content spreads more rapidly, exacerbating divisions within society.

Social media platforms unintentionally reinforce prejudices and discrimination, particularly among diverse cultural communities (Odell, 2019). This stems from platform designs that amplify polarized perspectives, thereby entrenching stereotypes, spreading hate speech, and promoting dehumanizing discourse (Rathje et al., 2021). While research acknowledges this issue (Paluck, 2009; White et al., 2021; Wong et al., 2022), most studies fail to address the complexities of modern digital media ecosystems and their influence on narrative perception.

With the increasing role of algorithmic curation and user participation, narratives in digital media are shaped not only by content but also by the medium, the messenger, and the platform's recommendation mechanisms (Ito 1997; McLuhan & Gordon, 2003). Information presentation determines audience perception, often leading to varying sentiment outcomes. For example, a video shared by a trusted source may foster empathy, while the same content, if framed negatively by an inflammatory influencer, may provoke hostility. Comments sections further influence viewers' emotional responses, either amplifying fear or fostering constructive engagement.

Case Study: YouTube's Algorithm and the 'Ethnic Neighbourhoods' Project

This presentation reports preliminary findings from Ethnic Neighbourhoods, a YouTube project designed to celebrate diverse immigrant communities. However, the study revealed how negative algorithmic curation can shape audience sentiment. YouTube's recommendation system frequently directs viewers from negative, sensationalist portrayals of specific neighborhoods toward documentary content meant to challenge those stereotypes. This unintended sequencing of narratives primes audiences to approach factual and positive content with skepticism or distrust, as they have already been exposed to biased perspectives beforehand.

Rather than fostering intercultural understanding, this algorithmic dynamic can frame corrective content as misleading or biased, simply because it contradicts the dominant narrative that the algorithm first introduced. Even as Ethnic Neighbourhoods sought to present authentic multicultural stories, YouTube often surfaced sensationalized or divisive related videos, reinforcing an "us vs. them" mentality. This case highlights a broader trend: algorithmic curation clusters people into ideologically insular communities, reinforcing pre-existing biases.

However, we also found that algorithmic curation is not inherently harmful. The same AI systems that intensify bias also provide opportunities for community-building and minority representation. For instance, the Ethnic Neighbourhoods channel successfully connected diaspora groups and helped them celebrate their heritage and identity. This reflects "bonding" social capital, which strengthens relationships within like-minded communities. However, without deliberate algorithmic interventions, bonding can turn into exclusion, deepening in-group/out-group divides.

What is largely missing from current AI design is a mechanism to promote "bridging" social capital—fostering meaningful connections across cultural or ideological lines. Without this, AI-driven content personalization will continue to reinforce social divisions, rather than facilitating understanding.

Beyond Engagement: Redefining Metrics for Human Flourishing

A kIto, 1997 #1013;White, 2021 #1000;Odell, 2019 #971;Rathje, 2021 #434;Paluck, 2009 #393;Wong, 2022 #496;McLuhan, 2003 #1014

Trust – Does the platform cultivate trust among users and in the information provided? Trust is a foundation for both business and society; without it, cooperation and commerce falter. Yet today's algorithms often prioritize virality over veracity,

undermining trust. New metrics could track the credibility of content (e.g. ratio of trustworthy information to misinformation) and user confidence in the platform's curation. Designing for trust might involve "showing reliable information" prominently and curbing the spread of falsehoods. Building trust also means transparency about how AI decides what we see.

Resilience – This refers to the community's ability to withstand and rebuff polarisation, misinformation, or malicious manipulation. A resilient digital space is one where users do not easily spiral into outrage or falsehood, and where diverse groups can weather disagreements without fragmenting. Redefining engagement to value long-term community health is critical. For example, platforms might measure the diversity of a user's content diet (as a proxy for openness) or the frequency of cross-cutting interactions. Research on social capital suggests that communities with more bridging ties are less polarised and more resistant to conspiracies and hatred. Thus, a platform's success could be measured in how well it facilitates bridging across social divides – helping people connect beyond their immediate tribe in positive ways.

Digital Ethics and Well-being – Beyond raw metrics, ethical principles should guide platform design. AI systems should be evaluated on fairness (are outcomes free of bias and discrimination?), accountability (can decisions be explained and audited?), and alignment with human values. The EU's guidelines for Trustworthy AI encapsulate this human-centric approach, viewing AI as a tool in the service of humanity and the public good, aimed at increasing individual and collective well-being (Need reference). In practical terms, this could mean an algorithm is judged not only by efficiency, but by its respect for user autonomy (e.g. allowing users more control over what the algorithm shows them) and its contribution to informed, ethical discourse. Business researchers and educators have a role to play in redefining these success criteria, drawing on interdisciplinary frameworks like ethics of care, stakeholder theory, and social psychology to inform what "good" AI behavior looks like on platforms.

Guiding AI-Driven Algorithm Toward Trust-Centered, Human-Focused Curation

Then how can we better guide AI in content platforms to prioritize human-centric outcomes over narrow optimisations? This presentation propose several recommendations for rethinking platform design and governance in the AI era:

Adopt Human-Centric Objectives: Platforms should explicitly integrate human well-being goals into their AI algorithms. Instead of optimising solely for clicks, incorporate objectives like increasing cross-community understanding or reducing the spread of harmful content. Concretely, an algorithm might be tuned to favor content that is engaging and enriching – e.g. promoting civil dialogue or educational value – over outrage bait.

Redesign Incentives and Metrics: Change what behavior the platform rewards. If polarisation is the byproduct of "popularity-based algorithms" chasing engagement, then broaden the metrics. For instance, reward content that users flag as constructive or trustworthy, even if it's not the most sensational. Internally, teams should track metrics like community trust, user well-being survey scores, or the prevalence

of bridging interactions. By measuring success in terms of social value created (e.g. connections built across cultures, accurate knowledge gained), companies can realign their growth with societal flourishing rather than division.

Foster Bridging and Diverse Exposure: Deliberately design recommendation engines to introduce diversity into the feed. Research shows that people with more cross-cutting social connections display lower levels of affective polarisation. Platforms could implement “bridging algorithms” – for example, recommending a video or post that offers a different but respectful perspective on a topic, or highlighting stories of collaboration across groups. Rather than trapping users in filter bubbles, the system would act more like a digital public square, exposing people to a variety of voices and shared experiences. This needs to be done carefully (to avoid forcing unwanted content), but even mild diversification can widen worldviews without sacrificing engagement.

In conclusion, transforming business education and research for the AI era entails embracing a vision of digital platforms that is ethical, human-centric, and conducive to trust. By redefining what we count and reward online, and by guiding AI with multidisciplinary wisdom, we can harness the power of algorithms to connect rather than divide. This presentation will seek deeper exploration of strategies to realign social media and other AI-driven systems with the highest ideals of business and society – enabling technology to be a force for coordination, flourishing, and harmony in the years ahead.

References

- Ito, J. 1997. Aesthetics of the Internet-Context as a Medium.
- White, F. A., Borinca, I., Vezzali, L., Reynolds, K. J., Blomster Lyshol, J. K., Verrelli, S. & Falomir-Pichastor, J. M. 2021. Beyond direct contact: The theoretical and societal relevance of indirect contact for improving intergroup relations. *Journal of Social Issues*, 77, 132-153.
- Odell, J. 2019. *How to do nothing : resisting the attention economy*, Brooklyn, NY, Melville House Publishing.
- Rathje, S., Van Bavel, J. J. & Van Der Linden, S. 2021. Out-group animosity drives engagement on social media. *Proceedings of the National Academy of Sciences*, 118, e2024292118.
- Paluck, E. L. 2009. Reducing intergroup prejudice and conflict using the media: A field experiment in Rwanda. *Journal of personality and social psychology.*, 96, 574-587.
- Wong, N. C. H., Massey, Z. B., Barbati, J. L., Bessarabova, E. & Banas, J. A. 2022. Theorizing prejudice reduction via mediated intergroup contact: Extending the intergroup contact theory to media contexts. *Journal of Media Psychology: Theories, Methods, and Applications*, 34, 89-100.
- Mcluhan, M. & Gordon, W. T. 2003. *Understanding Media: The Extensions of Man*, Gingko Press.
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TRANSFORMING BUSINESS EDUCATION WITH GENAI AVATARS: ENHANCING ENGAGEMENT, COLLABORATION, AND SOCIAL ENTREPRENEURSHIP

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Keywords: AI-Generated avatars, business education, experiential learning, social entrepreneurship, collaborative learning.

AI-generated avatar videos have the potential to be a disruptive and engaging tool in business education, enhancing content delivery, fostering deeper student participation, and promoting collaborative learning. These technologies offer new possibilities for interactive and immersive learning, allowing students to engage with complex topics while improving information retention and critical thinking (Aditya et al., 2023). AI-generated videos optimize educational material creation, making them adaptable to different learning styles and enhancing their contextualization in business education. Moreover, they reduce the workload of instructors while providing students with scalable, accessible, and highly engaging instructional resources (Denny et al., 2023). Understanding the perceptions of students and educators regarding AI-generated avatars is crucial, as their level of engagement with these tools directly influences their effectiveness in educational settings (Hao-yan et al., 2023). While AI-generated videos have been primarily used to enhance content delivery, their role in fostering peer interaction, socialization, and the development of an entrepreneurial mindset remains underexplored. As business education continues to evolve towards more experiential and collaborative learning models, AI-generated avatars offer an opportunity to reshape pedagogical approaches, making education more dynamic, personalized, and relevant to real-world business challenges.

Recent studies suggest that AI-generated videos featuring realistic avatars can significantly enhance student engagement and emotional connection with the learning process. While AI-generated instructors designed to resemble admired figures do not necessarily improve test performance, they have been shown to increase motivation and facilitate stronger learner engagement (Vallis et al., 2023). Other studies highlight the role of AI-driven learning environments in promoting reflection on ethical and social issues, further reinforcing their potential in business education (Pataranutaporn et al., 2022). Additionally, research on entrepreneurship education underscores the value of integrating technology-driven pedagogical approaches that enhance experiential learning and foster co-creation processes (Ramírez-Montoya et al., 2025). However, despite these promising insights, little research has been conducted on how AI avatars contribute to student collaboration, discussion, and engagement with social entrepreneurship concepts. This study seeks to address this gap by examining the impact of AI-generated avatars on student perceptions, peer interactions, and socialization in the context of a course on social entrepreneurship.

The research employed a mixed-methods approach to explore how AI-generated avatars influence student learning and engagement. A structured questionnaire was

administered to 135 MBA students enrolled in an online entrepreneurship course at a business school, with participants from different regions of Peru, assessing their perceptions of AI-generated avatars in educational videos. The survey examined engagement levels, motivation, and the effectiveness of these avatars in facilitating the understanding of social entrepreneurship concepts. Additionally, a qualitative analysis was conducted based on student contributions to a discussion forum, where they were asked to reflect on the characteristics of social entrepreneurs and provide real-world examples from their own contexts. This forum provided insights into how students engaged in peer interaction and conceptualized the role of social entrepreneurship in future ventures. The study applied methodological triangulation, integrating survey data with qualitative insights from forum discussions to offer a comprehensive perspective on AI's impact on business education. This approach allowed for an in-depth understanding of AI-generated avatars not only as content delivery tools but also as catalysts for student socialization, collaboration, and the development of entrepreneurial competencies.

Through this study, we seek to explore whether AI-generated avatars can enhance individual engagement and motivation, making the learning experience more accessible, interactive, and effective in helping students understand complex business concepts. Additionally, we will examine whether students who engage with AI-generated videos are more likely to participate actively in discussions, providing richer and more nuanced perspectives on social entrepreneurship. A key aspect of the research is determining whether the use of AI avatars in educational videos can help bridge the gap between theoretical concepts and practical applications, allowing students to draw connections between social entrepreneurship principles and real-world business scenarios.

This study aims to contribute to the growing body of research on AI in education by examining not only how AI-generated avatars improve content comprehension but also how they foster socialization and collaboration—an aspect often overlooked in AI-related education research. Unlike previous studies that focus on AI's role in enhancing knowledge acquisition, this research expands the scope by analyzing its impact on students' ability to understand and embody the role of a social entrepreneur. By integrating AI avatars into business curricula, this research highlights their potential to not only improve comprehension but also foster meaningful discussions, ethical reflection, and collaborative problem-solving—critical components of social entrepreneurship. The practical implications suggest that AI-generated avatars can serve as scalable, customizable learning tools that help business schools integrate innovative pedagogical models, fostering active learning and a deeper engagement with social impact-driven entrepreneurship. By providing a more immersive and interactive learning environment, AI avatars create new opportunities for students to engage with peers, exchange diverse perspectives, and critically reflect on the responsibilities and ethical dimensions of social entrepreneurship, essential competencies for driving sustainable business solutions.

Moreover, this research will contribute to understanding the importance of contextualized implementation strategies when integrating AI-generated avatars into business education, entrepreneurship training, and leadership development. While AI technology presents opportunities for innovation, its effectiveness will depend on

how well it is aligned with instructional goals and student learning needs (Portuguez-Castro, 2025). Findings from entrepreneurship education suggest that the impact of generative AI is closely tied to its alignment with task requirements and business objectives, highlighting the importance of technological adaptation in academic and professional contexts (Marchena Sekli & Portuguez-Castro, 2025). A key research question is whether AI personalization techniques—such as tailoring avatars to resemble mentors or industry leaders—can influence student motivation and learning effectiveness. Furthermore, we aim to explore the ethical and social implications of AI-driven learning environments, particularly in fostering responsible entrepreneurship and ethical decision-making.

As AI continues to evolve, this study will provide new opportunities to integrate generative AI into business education, particularly in areas such as social entrepreneurship, business ethics, and leadership training. By leveraging AI-generated avatars, educators may be able to design more engaging, accessible, and interactive learning experiences that go beyond traditional teaching methods. The ability of AI avatars to enhance both individual learning outcomes and peer collaboration positions them as a key enabler of pedagogical innovation in business education. By conducting this study, we aim to generate empirical evidence that AI-generated avatars are not only effective learning tools but also powerful mechanisms for fostering student collaboration, critical reflection, and social entrepreneurship competencies. As AI-driven learning environments continue to develop, their potential to reshape education will become increasingly significant, offering students immersive and dynamic experiences that prepare them for the challenges of an evolving global economy.

References

Aditya, J., Katz, A.S., Qadir, J. and Hingle, A. (2023). "Generative artificial intelligence and engineering education," *Journal of Engineering Education* 112(3), 572–577. <https://doi.org/10.1002/jee.20537>

Denny, P., Prather, J., Becker, B., Finnie-Ansley, J., Hellas, A., Leinonen, J., Luxton-Reilly, A., Reeves, B., Santos, E.A. and Sarsa, S. (2024). "Computing education in the era of generative AI," *Communications of the ACM*, 67(2), 56–67. <https://doi.org/10.1145/3624720>

Hao-yan, Y. and Yunyun, G. (2023). "Generative artificial intelligence empowers educational reform: current status, issues, and prospects," *Frontiers in Education*, 8. <https://doi.org/10.3389/feduc.2023.1183162>

Marchena Sekli, G. and Portuguez-Castro, M. (2024). "Fostering Entrepreneurial Success: Unleashing the Potential of Generative AI through Technology-to-Performance Chain. A Multi-case Study Approach," *Education and Information Technologies*. <https://doi.org/10.1007/s10639-025-13316-y>

Pataranutaporn, P., Leong, J., Danry, V., Lawson, A.P., Maes, P. and Sra, M. (2022). "AI-generated virtual instructors based on liked or admired people can improve motivation and foster positive emotions for learning," in *2022 IEEE Frontiers in Education Conference (FIE)*, 12–15 October, Uppsala, Sweden. IEEE, 1–9. <https://ieeexplore.ieee.org/document/9962478>

Portuguez-Castro, M. (2025) "Reimagining the future of business education through educational innovation," *Int. J. Markets and Business Systems* 5(2), 192–208.

Ramírez-Montoya, M.S., Casillas-Muñoz, F., Tariq, R., Álvarez-Icaza, I. and Portuguez-Castro, M. (2025). "Reimagining the future through the co-creation of social entrepreneurship in higher education: a multivariate prediction model approach," *Kybernetes*, 54(16), 1–19. <https://doi.org/10.1108/K-07-2024-1924>

Vallis, C., Wilson, S., Gozman, D. and Buchana, J. (2023). "Student perceptions of AI-generated avatars in teaching business ethics: We might not be impressed," *Postdigital Science and Education* 6, 537-555. <https://doi.org/10.1007/s42438-023-00407-7>

LEADING AND MANAGING IN THE AGE OF CO-INTELLIGENCE: SHAPING THE FUTURE WITH AI AND BUSINESS EDUCATION

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University of Louisville

Keywords: AI, business education, co-intelligence, strategy.

Proposal Overview

Building on our engaging participation in last year's conference, the University of Louisville College of Business continues to pioneer the integration of emerging technologies into business education. Our innovative curriculum combines rigorous academic foundations with real-world applications, preparing future leaders who can navigate technological disruption while maintaining human-centered leadership principles. We look forward to sharing our latest developments and insights at this year's conference.

Our Educational Philosophy

We've deepened our distinctive "town and gown" approach, which bridges academic excellence with practical business applications. This strategy has yielded remarkable results in several key areas:

1. Curriculum Evolution

Our business majors now engage in hands-on technology courses that emphasize practical application over theory. A popular university-wide elective draws students from diverse disciplines, creating rich discussions about technology's societal impact. Signature courses like "Managing the Future" incorporate contemporary works by thought leaders while grounding discussions in historical and philosophical perspectives. The increasing importance of soft skills such as critical thinking, problem solving, and communication in the age of Human-AI co-existence.

2. Industry Integration

We build industry-relevant AI teaching capacity through collaboration with industry experts. Local executives regularly share their experiences navigating technological transformation. Faculty research presentations connect academic insights with practical applications. Student-led discussions bridge classroom concepts with emerging career opportunities. Collaboration with industry to create learning opportunities through industry-led AI-Lab and AI Fellows.

3. Community Impact

We provide thought leadership through creating a platform for exchange and discussion of current AI-related issues. Cross-disciplinary initiatives unite business, humanities, and technical perspectives to address complex challenges.

Looking Forward

As returning participants, we're excited to deepen the conversations started last year and contribute to shaping the future of business education. Our experience

demonstrates how universities can prepare leaders who harness technology while preserving human wisdom and ethical decision-making. Our vision is for our school to create AI-Savvy business leaders of tomorrow.

Proposed Presentation outline

- First a bigger picture about AI and impact on education, especially business schools.
 - Second, the AI strategy for the College of Business; key objectives and key initiatives to achieve them
 - Third, challenges that we are facing and how we plan to address them
 - Fourth: closing with an optimistic note about the future of business education: AI-Savvy Business Leaders
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Session D3

**ETHICS, SAFETY
AND VERIFICATION**

A Panel Roundtable Discussion

Chair: Gregory Prastacos, Stevens Institute of Technology, USA

ETHICS, SAFETY AND VERIFICATION

A Panel Roundtable Discussion

Moderator:

- **Dr. Gregory Prastacos**, Professor of Management Science at the Stevens School of Business and former Dean (2012–2024), with a distinguished academic, research, and leadership career spanning Columbia University, Wharton, AUEB, and Stevens, recognized internationally for his contributions to analytics, digital transformation, and academic innovation.

Panel members:

1. **Dr. Theodore Evgeniou**, Professor at INSEAD and Director of its Executive Education programme Transforming Your Business with AI, with nearly 30 years of experience in Machine Learning and AI, spanning research, regulation, and business innovation, and holding four degrees from MIT..
2. **Dr. Daniel Hulme**, CEO Satalia, CEO Conscium, and Chief AI Officer WPP. He is a globally recognized expert in AI and an investor in emerging technologies. With over two decades of experience in AI, he has become a world-renowned keynote speaker and has been recognized as one of the top ten Chief AI Officers globally.
3. **Dr. Jannis Kallinikos**, Professor at LUISS University Rome and Professor Emeritus at the London School of Economics. He is an influential and interdisciplinary scholar known for his insightful and pioneering research on the impact of information technologies on organizations and institutions.

Abstract:

As artificial intelligence systems become more sophisticated and deeply integrated into business and public life, the need for robust frameworks around ethics, safety, and verification has never been more urgent. This roundtable convenes experts at the intersection of data, verification, and the implications of increasingly human-like AI behaviors to explore the intersections of technical reliability and moral responsibility in AI development.

The discussion will start by addressing how data nature and data quality impact AI system performance and safety, while also shaping public trust and organizational risk. The challenges posed by synthetic data, deep fakes, training data poisoning, or other adversarial manipulation will be presented and techniques to address them will be discussed.

The second part of the conversation will extend beyond immediate concerns about data integrity to more profound questions surrounding emergent behaviors and the evolving boundaries between human and machine agency. As AI systems begin to exhibit actions or capabilities that surpass their programmed parameters, new philosophical and practical dilemmas arise: Can systems be morally accountable? Should we treat sophisticated agents differently? How do we verify or contain systems whose behaviors cannot be fully predicted?

The third part of the conversation will address the question of how do we move from philosophy to practice. What are the trade-offs innovators or developers face between speed of deployment and verification rigor? What metrics or signals can help detect when systems are behaving in unanticipated ways? How do we bridge the gap between philosophical challenges of AI and real-world implementation? How do you maintain a balance between the need to innovate and the sometimes excessive or unclear regulatory environment?

Our aim is to have a forward-looking, multidisciplinary discussion that bridges theory and practice, and illuminates the challenges ahead but also offers pathways towards managing them responsibly.

Session A4

**TRANSFORMING HRM
THROUGH AI**

**Chair: Nancy Papalexandris, Athens University of Economics and
Business, Greece**

AI-POWERED SOLUTIONS FOR EMPLOYEE RETENTION WITHIN THE HR FRAMEWORK: TRENDS AND CHALLENGES

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Keywords: Artificial Intelligence, human resource management, employee retention, predictive analytics, HR technology.

Employee Retention in the Age of Artificial Intelligence

Employee retention has become a pressing challenge for modern organizations, with high attrition rates impacting financial performance, team cohesion, and long-term strategic goals. This study explores how Artificial Intelligence (AI) is transforming Human Resource Management (HRM) by introducing predictive, data-driven strategies to mitigate employee turnover. Grounded in the Human Capital Theory and the Resource-Based View (RBV), this research examines AI's role in enhancing talent retention by optimizing workforce analytics, career development strategies, and proactive intervention mechanisms.

A holistic literature review has been conducted to meet the aims of this research comprehensively. This study employed a systematic approach to article selection, ensuring a comprehensive and high-quality literature review. Indexed academic databases such as Scopus, Web of Science, and Google Scholar were used alongside industry reports and case studies from reputable sources. The review focused on publications from 2015 to 2024 to capture recent developments in AI-driven employee retention strategies. Articles were included if they examined AI tools for predicting and mitigating employee turnover, sentiment analysis, recommendation systems for career development, or ethical considerations in AI-driven HRM. Exclusion criteria eliminated studies lacking empirical insights, those unrelated to AI in HRM, and non-English sources without reliable translations. A two-stage screening process involved an initial review of titles and abstracts, followed by a full-text analysis for methodological rigor and relevance. Peer-reviewed journal articles, high-impact conference proceedings, and validated industry reports were prioritized to ensure the reliability of the findings.

Second, a case study analysis examined multinational organizations implementing AI-driven HRM solutions to assess their real-world impact. Data collection involved semi-structured interviews with HR managers and AI specialists, as well as analysis of retention metrics before and after AI adoption.

Third, a comparative study of AI-driven retention models evaluated key features, predictive accuracy, and employee engagement outcomes. Selected models included predictive analytics, sentiment analysis tools, and AI-driven career pathing systems (Gryniewicz, Zygała & Pilch, 2023). Performance metrics such as retention rates, employee satisfaction, and cost-effectiveness were analyzed across different organizational contexts. By integrating theoretical insights with empirical validation, this methodology provided a robust foundation for assessing the transformative potential of AI in employee retention strategies.

Current Trends in AI Applications for Employee Retention

The first objective of this study is to outline the emerging trends in the applications of AI relevant to employee retention strategies. One such major trend is the use of predictive analytics by HR teams in identifying potential turnover risks (Nandal et al, 2024). Predictive analytics applies historic and real-time data to provide actionable insights that support early intervention strategies. More importantly, this is the most feasible approach in analytics for behavioral data, performance metrics, and engagement trends in order to predict workforce reduction. As a sample of this, machine learning algorithms enable organizations to pinpoint patterns that intimate employee dissatisfaction or disengagement, thus allowing timely and strategic interventions.

Another notable development is the use of sentiment analysis, specifically if combined with techniques in Natural Language Processing. This combination has gained substantial traction as a robust monitoring tool in assessing employee morale. Organizations can get insight into employee sentiment and operational dissatisfaction in real time through textual data from employee surveys, internal communication platforms, and social media interactions. This capability lets HR professionals proactively address issues that otherwise could contribute to turnover, thus enhancing overall retention rates.

AI-based recommendation systems are one of the most important trends in employee retention strategies (Johnson, Stone & Lukaszewski, 2020). These work in mitigating the loss of vital human capital through the exit of employees from the organization. Incentive systems are further refined with the inclusion of AI, which enables personalized career development by considering the analysis of skills, performance contexts, and career aspirations, as well as the demands of an organization. This personalized approach not only encourages employee satisfaction but also plays a very important role in aligning individual and organizational objectives, thus improving retention outcomes.

The literature also underlines the role of AI in enhancing onboarding processes. AI-driven tools, such as chatbots, offer real-time feedback to new recruits, making their adjustment to the organizational environment much easier. Such technologies also foster fairness by eliminating subconscious biases in human resources decision-making in order to eventually develop a nondiscriminatory working culture.

Challenges in Integrating AI into HRM Practices

Despite the promising potential of AI in changing how employee retention strategies are designed, the literature has pointed out several challenges related to integrating AI into HRM practices. First, there is an issue of data protection and ethical consideration. As more organizations rely on AI to analyze sensitive employee data such as performance evaluations, engagement surveys, and feedback mechanisms, questions arise about consent (Nishar, 2023).

The integration of AI into human resource management practices has wider ramifications in relation to organizational culture, employee perceptions, and decision-making processes (Sabil et al, 2023). Highlighted in the literature is the importance of evaluating the effects that the adoption of AI has on the cultural climate of organizations. For instance, although predictive models may identify prospects with

a heightened vulnerability to risk, it is an empathetic, human intervention contextually aware that identifies root causes for their discomfort. Organizations that will be able to balance AI integration without losing the human touch in HRM might achieve higher levels of trust and respect among their employees.

Any successful AI adoption strategy in HRM requires that transparency and ethical governance be guiding principles. There is a need, according to the literature, for clear policies regarding data protection—for instance, collecting, using, and storing information related to employees. Strong frameworks should be developed that ensure privacy and compliance with legal regulations, such as the General Data Protection Regulation, in order to reduce the concerns about data misuse and maintain ethical standards (Malik, Budhwar & Kazmi, 2023).

The literature further suggests that organizations should adopt a dual approach in AI adoption, considering the transformative potential of AI along with human-centeredness. This duality is particularly important within the domain of HRM, where reliance on AI reinforces decision-making through data-driven insights and yet maintains the importance of interpersonal relationships and human empathies.

Conclusion and Future Directions

This study emphasizes how AI has the potential to bring transformational change in employee retention strategies in human resource management practices. AI-driven technologies are offering innovative solutions to organizations in handling different challenges arising due to high attrition rates. By utilizing predictive analytics, sentiment analysis, and personalized recommendation systems, an organization can proactively mitigate turnover risks and develop a more engaged and satisfied workforce.

However, the successful implementation of AI into HRM depends on an all-around understanding of the challenges associated with it, including ethical issues, data privacy, and dynamics of organizational culture. For organizations to get around these complexities, transparency, ethical governance, and the insertion of human judgment will be required in major AI-driven decisions.

Building on the study's findings, future research should explore:

- AI's long-term impact on employee retention through longitudinal studies
- AI's influence on organizational culture and balancing AI efficiency with human-centered HR practices
- Ethical and legal concerns, including data privacy, algorithmic bias, and regulatory compliance
- AI's role in employee well-being (stress, burnout, job satisfaction)
- Effectiveness of AI-based career development systems
- Comparative studies across industries and impact in hybrid/remote work environments

These directions will contribute to ethical, employee-centric AI adoption, ensuring sustainable workforce management strategies.

Indicative References

- Gryniewicz, W., Zygała, R., & Pilch, A. (2023). AI in HRM: case study analysis. Preliminary research. *Procedia Computer Science*, 225, 2351-2360.
- Johnson, R., Stone, D., & Lukaszewski, K. (2020). The benefits of ehrm and ai for talent acquisition. *Journal of Tourism Futures*, 7(1), 40-52.
- Malik, A., Budhwar, P., & Kazmi, B. A. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review*, 33(1), 100940.
- Nandal, M., Grover, V., Sahu, D., & Dogra, M. (2024). Employee Attrition: Analysis of Data Driven Models. *EAI Endorsed Trans. Internet Things*, 10, 1-10.
- Nishar, S. (2023). The role of artificial intelligence in transforming human resource management: a literature review. *Design of Single Chip Microcomputer Control System for Stepping Motor*, 1-4.
- Sabil, S., Bangkara, B. A., Moge, T., Niswan, E., & Timotius, E. (2023). Identification of hrn improvement strategy using artificial intelligence in modern economic development. *International Journal of Professional Business Review*, 8(6), e01835.
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HUMAN RESOURCE MANAGEMENT IN THE DIGITAL ERA: INSIGHTS FROM HR PROFESSIONALS IN GREECE

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Keywords: Human resource management, artificial intelligence, digital transformation, talent acquisition.

Introduction

In the rapidly evolving digital landscape, Human Resource Management (HRM) is undergoing a profound transformation driven by technological advancements. One of the most influential developments is the integration of Artificial Intelligence (AI) into key HR functions, such as talent acquisition and selection. The implementation of HR technology is primarily driven by the need to improve effectiveness, streamline operations, and align with organizational objectives (Touriano et al., 2023; Okatta, Ajayi and Olawale, 2024). As HR's role becomes increasingly important at the highest levels of organizational leadership, expectations for professionals have risen significantly (Schiemann and Ulrich, 2017). Today, HR professionals are expected to drive technological adoption, foster innovation, support evolving work models, and play a crucial role in attracting, retaining, and developing the workforce of the future (World Economic Forum, 2019). They must move beyond their traditional administrative roles to become impactful strategic partners and key drivers of organizational success (da Silva et al., 2022). By examining the perspectives of HR professionals across various industries in Greece, the present study aims to explore how digital tools and AI are reshaping HR practices, providing a critical analysis of the emerging trends, challenges, and opportunities that accompany this digital shift.

Research Purpose

The present study examines the transformative impact of digitalization on HRM, with a particular focus on the role of AI. Specifically, it aims to identify contemporary challenges and trends that shape modern HR practices, alongside the evolving roles and skills required in an ever-changing digital business environment, as perceived by HR professionals. The study investigates the digital transformation of HRM, analyzing its core components, tools, and drivers that encourage the adoption of digital technologies in HR operations, along with the barriers encountered during their implementation. Special attention is given to AI's role in talent acquisition, evaluating its practical applications, potential benefits, and the challenges it presents, especially in relation to ethics, legal compliance, as well as the candidate experience and trust.

Methodology

The research followed a qualitative approach, focusing on exploring HR professionals' experiences, perceptions, and practices regarding the impact of digital transformation and AI on HRM. A total of 23 participants were selected through purposive

sampling, a non-probability technique, targeting HR professionals with relevant expertise and experience, particularly in digital transformation and AI integration. This sampling approach helped enhance the validity and reliability of the research by enabling the collection of rich, in-depth data from individuals with direct experience in the subject matter (Gioia, Corley and Hamilton, 2013). Participants were chosen based on specific criteria, such as their roles across various HR functions (e.g., Recruiting, Training & Development, Performance Management, Payroll) and hierarchical levels (mid, senior, and executive), ensuring a comprehensive representation. They were identified using the “HR Powerlists” published by Boussias, a leading B2B trade publishing and events company in Greece. These lists highlight influential HR professionals recognized for their contributions to the HR community in Greece during 2022 and 2023.

Data collection was conducted through semi-structured interviews, allowing flexibility in exploring the participants’ experiences while ensuring consistency across interviews (Bell, Bryman and Harley, 2022). An interview guide containing open-ended questions was designed to prompt discussions on key themes, including: a) current HR challenges, b) the ongoing digital transformation and its impact on HR operations, c) the evolving skill sets required for HR professionals, and d) the role of AI in recruitment and decision-making. The interviews lasted between 45 and 60 minutes and were conducted via cloud-based video conferencing platforms such as Microsoft Teams and Google Meet. With participants’ consent, the interviews were audio recorded and subsequently transcribed for analysis. The process took place between May and September 2024, continuing until data saturation was reached, meaning no new insights emerged from subsequent interviews (Creswell and Creswell, 2017). The interview data were analyzed using thematic analysis, supported by the qualitative data analysis software “NVivo 15”. Using NVivo 15 allowed for the systematic coding and synthesis of the interview transcripts, facilitating the identification of themes and the extraction of key insights.

Main Findings

HR Challenges and Trends in the Digital Era

Modern HRM faces various challenges and trends that impact organizational performance and strategy. Among the key challenges mentioned were talent acquisition and retention, especially in high-demand sectors like technology, where specialized professionals remain scarce. Managing multigenerational teams with diverse expectations and skill levels was also identified as a recurring issue. Participants further highlighted the growing importance of flexible work models, such as hybrid and remote work, which have become a standard expectation following the pandemic, particularly among younger employees. Other critical issues raised included employee well-being, effective team communication, and adapting to labor laws and work environment changes. Respondents emphasized the importance of balancing employee needs with business goals, prioritizing diversity and inclusion, and fostering continuous learning to maintain resilience in an ever-changing landscape. In addition, the digital transformation of HRM was identified by most participants as a significant trend, accompanied by considerable challenges. It was described as a

process that extends beyond simple task digitalization, encompassing a fundamental reengineering of HR processes.

Changing HR Roles and Critical Skills for the Digital Era

According to participants, HR professionals in the digital era should act as catalysts for change by effectively communicating transformation goals, supporting employee training, and staying updated on industry trends. They must also adapt by embracing data-driven decision-making, acquiring technical and financial expertise, and promoting digital literacy within the workforce. Key skills mentioned include critical thinking, change management, and empathy, enabling HR to mediate between employees and leadership during transitions.

Digital HRM: Opportunities, Benefits, and Implementation Barriers

Participants highlighted several key aspects and benefits of this transformation, with the majority focusing on the automation and optimization of HR processes. In most HR departments, digital transformation has already transformed key functions such as recruitment, training, and HR reporting, optimizing workflows and increasing efficiency. Cloud-based systems and self-service portals provide 24/7 access to HR services, while AI-driven tools are enhancing areas such as recruitment, performance management, data visualization, workforce planning, and predictive analytics. The benefits of digital tools include increased efficiency, reduced errors, improved communication, and better data insights for strategic decision-making. However, challenges such as the complexity of customizing software, resistance to change, lack of digital skills, and concerns over cybersecurity and data privacy were noted as significant barriers by HR professionals. Overcoming these obstacles requires effective internal communication, continuous training, and strong change management practices.

AI's Impact on Recruitment Processes

Respondents expressed mixed views regarding the application of AI in recruitment processes. While many acknowledged AI's potential in automating routine tasks like job ad creation, resume screening, and psychometric testing, they also highlighted its current limitations. Common concerns included errors in resume filtering due to diverse formatting, lack of emotional intelligence, and the inability to fully assess cultural fit or soft skills. They also expressed concerns about the impact of AI usage in recruitment processes on candidates' trust and employer branding. Candidates familiar with AI tools might view its use positively, associating it with innovation and objectivity, while less familiar or skeptical candidates may perceive it as impersonal or unreliable. Excessive automation and lack of personal touch could harm a company's image, making candidates feel undervalued. Participants emphasized the need for careful and context-specific implementation of AI to maintain trust and a positive employer reputation. Most agreed that AI should play a supplementary role, assisting human recruiters rather than replacing them. Significant ethical and legal challenges associated with the use of AI in recruitment processes were also identified. Ethical concerns included potential bias and discrimination arising from the data used to train AI systems, which could perpetuate stereotypes, such as gender disparities in specific job roles. There were also worries that fully automated AI

processes might limit candidates' ability to demonstrate essential personal qualities, particularly those not easily measurable by AI. On the legal side, compliance with GDPR was emphasized, with a focus on obtaining consent and securely managing personal data. Concerns were also raised about accountability when AI systems make decisions, especially in cases of discrimination or ethical dilemmas.

Conclusion

The findings can provide valuable insights for HR professionals and organizational leaders, guiding them in navigating the digital era effectively, preparing for contemporary challenges, and promoting innovation and adaptability within their teams. It thoroughly examines the opportunities and challenges associated with digital transformation and AI adoption in HR, highlighting the importance of a balanced approach that enhances operational efficiency while maintaining a human-centric perspective to ensure sustainable organizational growth. Additionally, this study contributes to the relatively underexplored area of AI in HR, particularly in the context of Greece, thus addressing a notable gap in the existing literature.

References

- Bell, E., Bryman, A. and Harley, B. (2022). *Business research methods*. Oxford University Press.
- Creswell, J.W. and Creswell, J.D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.
- Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013). 'Seeking qualitative rigor in inductive research: Notes on the Gioia methodology', *Organizational Research Methods*, 16(1), pp. 15–31.
- Okatta, C.G., Ajayi, F.A. and Olawale, O. (2024). 'Navigating the future: integrating AI and machine learning in hr practices for a digital workforce', *Computer Science & IT Research Journal*, 5(4), pp. 1008–1030.
- Schiemann, W.A. and Ulrich, D. (2017). 'Rise of HR—New mandates for IO', *Industrial and Organizational Psychology*, 10(1), pp. 3–25.
- da Silva, L.B.P. et al. (2022). 'Human resources management 4.0: Literature review and trends', *Computers & Industrial Engineering*, p. 108111.
- Touriano, D. et al. (2023). 'The Role of Information Technology in Improving the Efficiency and Effectiveness of Talent Management Processes', *Jurnal Minfo Polgan*, 12(1), pp. 539–548.
- World Economic Forum (2019). *HR4.0: Shaping People Strategies in the Fourth Industrial Revolution*, World Economic Forum. Available at: https://www3.weforum.org/docs/WEF_NES_Whitepaper_HR4.0.pdf (Accessed: 13 January 2022).

FROM DATA TO COMPETITIVE SUCCESS THROUGH PEOPLE: THE AMO FRAMEWORK

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Keywords: HR analytics, AMO framework, competitive advantage, PLS-SEM.

Human Resource Analytics (HRA) has been suggested as a successful tool for organizations to respond to uncertainty and enhance competitiveness (Marler and Boudreau, 2017, McCartney et al., 2021). It is defined as “the dynamic organizational capability and HRM practice of utilizing people data and integrating financial perspectives to explain and predict valuable and relevant business insights and external benchmarks, and to inform actionable and competitive strategic decision-making” (Chousmekeridou and Galanaki, 2023). Increasingly recognized as an indispensable tool for HR management (HRM) function (Hamilton and Sodeman, 2020), HRA is viewed as a strategic partner and a critical decision enabler (Sousa, 2018; Dahlbom et al., 2020).

Despite its potential, HRA continues to face significant challenges, that hinder its broader deployment and advancement (Dahlbom et al., 2020). One major issue is the limited explanations of how, where and when HRA can be effectively deployed (Espegren and Hugosson, 2023). This gap prevents researchers from drawing general conclusions and fully unlock its value in the HRM context. It also points to the limitations of the theoretical frameworks that have been used (Conboy, Dennehy and O'Connor, 2020). When it comes to the benefits of HRA deployment, while evidence-based decision-making value is well documented in non-HR-related corporate functions (Lismont et al., 2017), HR managers stick to their intuition and generally recommended practices to get a sense of things, rather than relying on analytical insights. This is a common pattern in departments often characterized by a high rate of personal involvement, such as HRM (Matzler, Uzelac and Bauer, 2014). The slow pace of HRA deployment (HRAD) is linked to the absence of well-defined practices and resistance of organizations to swift and modify their long-established norms (Chattopadhyay, Biswas and Mukherjee, 2017). However, the significant growth of HR information systems (HRIS) is gradually changing the way HRM professionals address various challenges within the HRM function (Simón and Ferreira, 2018).

The objective of the study is to examine the factors that connect HRAD with business outcomes. Following the line of research on data analytics deployment, we focus on the intersection of two key areas: (1) data-driven and (2) people-centric analytics. We examine the potential of HRAD within firms by adopting data-driven strategies that have proven effective in other business areas, such as marketing or finance. We argue that firms with well-established evidence-based management (EBM) practices, competitive pressure (CP) and strategic role of HRM department will be more likely to deploy and leverage such practices in HRM and enhance busi-

ness outcomes. We apply the Ability, Motivation, and Opportunity (AMO) framework at the organizational level (Appelbaum et al., 2000), to explore the significance of adopting AMO behaviors in deploying HRA to achieve sustainable competitive advantage. Not many studies have applied this framework to explore the deployment factor (Hersyah and Hadining, 2020). We argue that AMO allows for the integration of factors, such as ability (e.g., data analytics skills and EBM), motivation (e.g., industry dynamism and competitive pressure) and opportunity (e.g., data availability and symbolic HRM) within a unified framework, something that has been separately discussed in previous studies (e.g., ability-dynamics capability framework, motivation and opportunity-TAM, TOE).

We define EBM as a signal of the company's analytics ability, encompassing three dimensions; data analytics skills (ability), industry dynamism (motivation) and data availability (opportunity). We argue that companies fostering EBM require employees to be able to have strong technical, relational and business skills, otherwise data analytics skills, to capture and apply evidence (Mikalef et al., 2019). In addition, operating in highly dynamic industries, where the need to survive and the risk of losing profits and market share are significantly higher (Chung et al., 2021), motivates companies to seek evidence, navigate uncertainty and maintain competitiveness (Rahman et al., 2023). Furthermore, access to diverse data sources, internally and externally, provides action opportunities for EBM practices (Gupta and George, 2016).

At the same time, we conceptualize HRAD as a composition of evidence-enhancing, competition-driven and departmental-enabled practices. Firms relying on EBM can effectively capture the right people data, ask the right people-related questions, apply relevant HR metrics and systematically translate HR-related insights into actionable outcomes for stakeholders (McCartney and Fu, 2023). Using the existing EBM practice as a retooling tool for HRM, we emphasize its importance, as an ability factor for HRAD and sustainable competitive advantage (Wamba et al., 2017). As HRA is still considered an innovation (Peeters, Paauwe and Van De Voorde, 2020), its deployment is often considered a strategic tool for competing in the marketplace. We assume that companies facing high competitive pressure are more likely to deploy HRA at an organizational level. Therefore, competition is a critical motivational driver for HRAD. Last, the opportunity factor in the AMO framework for HRAD is reflected in HR's role in formulating strategy and shaping strategic decisions, an area that is underexplored in research regarding HRAD (Hermans and Ulrich, 2021). Such activities primarily focus on the HRM function itself, reflecting an attempt to position and establish it as a key strategic partner within organizations (Hermans and Ulrich, 2021, p. 1064).

An online questionnaire was developed and distributed online. The survey targeted a sample of 174 HRA Professionals in June 2024, through Qualtrics panel service, utilizing a 5-point Likert scale (ranging from 1-strongly disagree to 5-strongly agree). We formulated six hypotheses that were tested using Partial Least Square Structural Equation Modeling (PLS-SEM). All constructs were measured using validated and published scales except for the HRAD scale which was first introduced in this study. The scale was designed and validated across six different HRM areas, following the proposition of Marr (2018), (1) data-driven recruitment, (2) data-

driven employee engagement, (3) data-driven safety and wellness, (4) data-driven learning and development, (5) data-driven performance management, and (6) future data-driven HRM (Marr, 2018). The measurement model assessment criteria were confirmed for all constructs (Reflective: factor loadings and AVE values ≥ 0.5 , CA and CR ≥ 0.7 , Fornell-Larcker criterion and HTMT ≤ 0.9 , Formative: VIFs ≤ 3.3) (Fornell and Larcker, 1981, p.46, Lance et al., 2006, Hair et al., 2009, Kock, 2015, Hair et al., 2019). In addition, structural model met all required assessment metrics with most hypotheses to be significant at the 0.000 point level, with good model power and fit ($R^2 \geq 0.40$, $Q^2 \geq \text{zero}$, estimated model ≤ 0.08) (Shmueli and Koppius, 2011). No common method bias was detected, based on the VIF values and Harman's single factor test (37.346%, below the threshold of 50%, Podsakoff, 2003).

The findings of this study reveal a positive and statistically significant relationship between AMO factors and the analytics paradigm. Specifically, EBM is positively linked to employee data analytics skills (Shamim et al., 2020), industry dynamism (Rahman et al., 2023) and data availability (Cao, Duan and El Banna, 2019). In addition, companies already utilizing EBM, with strong HRM departments (McCartney and Fu, 2023) and competitors deploying HRA (Marler and Boudreau, 2017), are more likely to deploy HRA, thereby enhancing their sustainable competitive advantage.

The results of this study provide valuable insights into continuous calls for deeper insights on HRA and business outcomes, determining both direct and indirect paths (van den Heuvel and Bondarouk, 2017). At a methodological point of view, we introduce a new measurement scale for HRA deployment, that, unlike previous studies that focus on the extent of HRA use (Thakur et al., 2024), it offers a function-specific measurement scale. Regarding the theoretical contribution, we argue that AMO allows for the connection between the HRA deployment, as a set of AMO-aligned (-enhancing, -driven and -enabled) practices, and organizational competitiveness (Alkhalaf and Al Tabbaa, 2024). In addition, the application of the theory on a technical-centric (data analytics), while maintaining its applicability on people-centric (HRM) analytics, advocates for the integration of frameworks traditionally used in the business literature, into the information technology field. This approach, supporting the hypotheses, underscores the potential for bridging the different focuses of analytics, paving the way for a more holistic approach to HRAD and sustainable competitive advantage. From a practical point of view, the study emphasizes the significance of the symbolic HRM on the final decision, which serves as the voice of the department in the process of technology-innovation adoption. Last, we differentiate HRA from other analytical domains, by highlighting the importance of having a balanced skills set, including both hard (analytics-related) and soft (HRM-related) skills to effectively deploy HRA. Specifically, the curvilinear effect found of data analytics skills on EBM, might be relevant to the risk of analysis-paralysis, as highlighted by both researchers and practitioners, narrowing understanding of complex situations (Farrell, 2023). This phenomenon might decrease resistance and fear and foster a more welcoming environment towards HRA's embracement in organizations.

The current study has some limitations to be considered. First, the use of the Qualtrics survey panel limits the generalizability of the findings. In addition, fac-

tors, such as technology competence or data culture, that could affect HRAD, are not captured in this study. Future research could explore these aspects, along with conducting a longitudinal study, and examine the effects of HRAD impacts over time.

References

Alkhalaf, Taher, and Omar Al-Tabbaa. 2024. The effect of ability, motivation and opportunity (AMO) on SMEs' innovation performance. *Creativity and Innovation Management* 33: 21–38. [CrossRef]

Appelbaum, E. et al. (2000) *Manufacturing advantage: Why high performance systems pay off*. New York: ILR Press Cornell University Press.

Cao, G., Duan, Y. and El Banna, A. (2019) 'A dynamic capability view of marketing analytics: Evidence from UK firms', *Industrial Marketing Management*, 76, pp. 72–83. doi: 10.1016/j.indmarman.2018.08.002.

Chattopadhyay, D., Biswas, D. D. and Mukherjee, S. (2017) 'A new look at HR analytics', in *Globsyn Management Journal*, pp. 41–51.

Chousmekeridou, R. and Galanaki, E. (2023) 'A qualitative analysis of the HR analytics insight: experiences from the line', in *European Academy of Management Proceedings*.

Chung, H. F. L. et al. (2021) 'Dynamism and B2B firm performance: The dark and bright contingent role of B2B relationships', *Journal of Business Research*, 129, pp. 250–259. doi: 10.1016/j.jbusres.2021.02.047.

Conboy, K., Dennehy, D. and O'Connor, M. (2020) "“Big time”: An examination of temporal complexity and business value in analytics', *Information and Management*, 57(1). doi: 10.1016/j.im.2018.05.010.

Dahlbom, P. et al. (2020) 'Big data and HR analytics in the digital era', *Baltic Journal of Management*, 15(1), pp. 120–138. doi: 10.1108/BJM-11-2018-0393.

Espgren, Y. and Hugosson, M. (2023) 'HR analytics-as-practice: a systematic literature review', *Journal of Organizational Effectiveness*. doi: 10.1108/JOEPP-11-2022-0345.

Farrell, M. (2023) *Data and Intuition: Good Decisions Need Both.*, Harvard Business Publishing. Available at: <https://www.harvardbusiness.org/data-and-intuition-good-decisions-need-both/> (Accessed: 22 January 2025).

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18, 39–50.

Gupta, M. and George, J. F. (2016) 'Toward the development of a big data analytics capability', *Information and Management*, 53(8), pp. 1049–1064. doi: 10.1016/j.im.2016.07.004.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis* (7th ed.). Prentice-Hall.

Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019), "When to use and how to report the results of PLS-SEM", *European Business Review*, Vol. 31 No. 1, pp. 2-24.

Hamilton, R. H. and Sodeman, W. A. (2020) 'The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources', *Business Horizons*, 63(1), pp. 85–95. doi: 10.1016/j.bushor.2019.10.001.

Hermans, M. and Ulrich, M. D. (2021) 'How symbolic human resource function actions affect the implementation of high-performance work practices: The mediating effect of influence on strategic decision-making', *Human Resource Management Journal*, 31(4), pp. 1063–1081. doi: 10.1111/1748-8583.12361.

Hersyah, M. H., & Hadining, A. (2020). The Effect of Motivation-Opportunity-Ability (MOA) Framework in SME's Social Media Marketing Adoption. *International Journal of Innovation in Enterprise System*, 4(1), 66–77. Retrieved from <https://ijies.telkomuniversity.ac.id/index.php/IJIES/article/view/49>

van den Heuvel, S. and Bondarouk, T. (2017) 'The rise (and fall?) of HR analytics', *Journal of Organizational Effectiveness: People and Performance*, 4(2), pp. 157–178. doi: 10.1108/joepp-03-2017-0022.

Kock, N. (2015), "Common method bias in PLS-SEM: a full collinearity assessment approach", *International Journal of e-Collaboration (Ijec)*, Vol. 11 No. 4, pp. 1-10.

Lance, C. E., Butts, M. M., & Michels, L. C. (2006). The sources of four commonly reported cutoff criteria: What did they really say? *Organizational Research Methods*, 9, 202–220.

Lismont, J. et al. (2017) 'Defining analytics maturity indicators: A survey approach', *International Journal of Information Management*, 37(3), pp. 114–124. doi: 10.1016/j.ijinfomgt.2016.12.003.

Marler, J. H. and Boudreau, J. W. (2017) 'An evidence-based review of HR Analytics', *The International Journal of Human Resource Management*, 28(1), pp. 3–26. doi: 10.1080/09585192.2016.1244699.

Marr, B. (2018) *Data-driven HR: how to use analytics and metrics to drive performance*. 1st edn. Kogan Page.

Matzler, K., Uzelac, B. and Bauer, F. (2014) 'Intuition: The missing ingredient for good managerial decision-making', *Journal of Business Strategy*, 35(6), pp. 31–40. doi: 10.1108/JBS-12-2012-0077.

McCartney, S. and Fu, N. (2023) 'Enacting people analytics: Exploring the direct and complementary effects of analytical and storytelling skills', *Human Resource Management*, pp. 1–19. doi: 10.1002/hrm.22194.

McCartney, S., Murphy, C., & McCarthy, J. (2021). 21st century HR: a competency model for the emerging role of HR Analysts. *Personnel review*, 50(6), 1495-1513.

Mikalef, P. et al. (2019) 'Configurations of big data analytics for firm performance: An fsQCA approach', 25th Americas Conference on Information Systems, AMCIS 2019, (December 2020).

Minbaeva, D. (2021) 'Disrupted HR?', *Human Resource Management Review*, 31(4). doi: 10.1016/j.hrmr.2020.100820.

Oliveira, T. and Martins, M. F. (2010) 'Information technology adoption models at Firm Level: Review of literature', 4th European Conference on Information Management and Evaluation, ECIME 2010, 14(1), pp. 312–322.

Oliveira, T., Thomas, M. and Espadanal, M. (2014) 'Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors', *Information and Management*, 51(5), pp. 497–510. doi: 10.1016/j.im.2014.03.006.

Peeters, T., Paauwe, J. and Van De Voorde, K. (2020) 'People analytics effec-

tiveness: developing a framework', *Journal of Organizational Effectiveness*, 7(2), pp. 203–219. doi: 10.1108/JOEPP-04-2020-0071.

Podsakoff, N. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, p. 10.1037.

Rahman, M. S. et al. (2023) 'Technology readiness of B2B firms and AI-based customer relationship management capability for enhancing social sustainability performance', *Journal of Business Research*, 156(December 2021), p. 113525. doi: 10.1016/j.jbusres.2022.113525.

Shamim, S. et al. (2020) 'Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms', *Technological Forecasting and Social Change*, 161. doi: 10.1016/j.techfore.2020.120315.

Shmueli, G. and Koppius, O.R. (2011), "Predictive analytics in information systems research", *MIS Quarterly*, Vol. 35 No. 3, pp. 553-572.

Simón, C. and Ferreira, E. (2018) 'Workforce analytics: A case study of scholar–practitioner collaboration', *Human Resource Management*, 57(3), pp. 781–793. doi: 10.1002/hrm.21853.

Sousa, M. J. (2018) 'HR analytics models for effective decision-making', *Proceedings of the 14th European Conference on Management, Leadership and Governance, ECMLG 2018*, (2004), pp. 256–263.

Thakur, S.J., Bhatnagar, J., Farndale, E. and Aeron, P. (2024), "Human resource analytics, creative problem-solving capabilities and firm performance: mediator moderator analysis using PLS-SEM", *Personnel Review*, Vol. 53 No. 7, pp. 1687-1709. <https://doi.org/10.1108/PR-11-2021-0809>

Wamba, F. S. et al. (2017) 'Big data analytics, dynamic capabilities and firm performance', *Journal of Business Research*, 70, pp. 356–365. doi: 10.1108/MD-08-2019-020.

Session B4

AI IN MANUFACTURING

Chair: Panos Repoussis, Athens University of Economics and Business,
Greece

AI-POWERED DRUG DEVELOPMENT: A DIGITAL INNOVATION FRAMEWORK

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Keywords: Digital twins, large language models, hybrid modeling, AI knowledge tools, biologics manufacturing.

The rapid evolution of pharmaceutical development necessitates innovative approaches to address the increasing complexity of processes, particularly in biologics manufacturing. At AstraZeneca, our recent work on the Large Scale Platform Dryer (LSPD) aligns with the principles laid out in our earlier conference proceedings following the LMDE 2023 on digital twins, mechanistic and hybrid modeling, and the transformative potential of large language models (LLMs) – effectively pointing to a holistic digital twin of our business. This vision is now starting to take shape through our AI-Powered Drug Development program in AstraZeneca. Building on the methodologies and insights presented in the LMDE 2023 paper, this extended abstract highlights the application of cutting-edge digital science to biologics manufacturing while addressing the critical need for accessible process knowledge through AI-powered drug development tools.

Hybrid Modeling: Bridging Mechanistic and Statistical Approaches

True to the framework described in our previous research, the development of the LSPD process model exemplifies the integration of mechanistic understanding, hybrid modeling, and black-box statistical (AI) models. By leveraging first principles and thermodynamic fundamentals, the LSPD model correlates feedstock properties, atomized droplet size, and drying kinetics to predict critical powder quality attributes. This mechanistic foundation is augmented by machine learning models trained on experimental and real-world datasets, creating a predictive tool capable of navigating the complexity of biologics manufacturing.

Our achievements to date include a Mechanistic-Driven Model Design. Built from first principles, the model ensures scalability across formulation strengths and future products, embodying the principles of mechanistic modeling outlined in our previous work. We perform Hybrid Modeling Across Scales by combining mechanistic and statistical approaches, which allows the model to support spray drying processes from laboratory to commercial scales, enabling accelerated development timelines and robust process optimization. The model has been deployed as a user-friendly web app, providing seamless access to predictive capabilities. This integration aligns with the concept of digital twins as predictive, dynamic replicas of physical systems outlined in our earlier research.

Future plans aim to enhance the model's predictive power by continuously re-training it with new data, extending its application to porous particle processes, and integrating it into an end-to-end digital twin framework that links formulation and process parameters as well as simulated LSPD operations to final product CQAs.

AI Knowledge Navigation: Large Language Models in Action

In parallel, our work on an ‘AI Knowledge Navigator’ demonstrates the application of LLMs organizing and amplifying knowledge within AstraZeneca’s operational ecosystem. The tool addresses the challenge of scattered technical information by providing a natural language interface with plans to integrate multimodal inputs (e.g., text, structured data, and links) to deliver precise answers and guide users to relevant documents. This aligns with the role of LLMs as orchestrators of digital twins, as described in our earlier research.

Key features of the current implementation include:

1. **Specialized Knowledge Base:** A curated repository focused on the LSPD, consolidating hundreds of documents into a single accessible platform and plans for integrate additional key repositories content.
2. **Troubleshooting Optimization:** The tool reacts to a user’s query and thereby assists with common operational questions, with plans for leveraging the predictive capabilities of LLMs for real-time troubleshooting.
3. **Traceable Outputs:** Responses include direct links to source documents, ensuring transparency and context for decision-making.
4. **Scalability and Security:** Built on a scalable four-tier environment with robust authentication and compliance measures.

Future enhancements will include advanced role-based access controls, improved business process understanding, the ability to analyze and interpret image data as well as include other languages than english. These developments will not only improve answer quality but also expand the knowledge navigator’s domain to other key manufacturing processes.

The AI Knowledge Navigator in the Context of Digital Twins

The AI tool is an integral part of LLM-integrated digital twins, serving as an intelligent intermediary between data repositories and end-users. By linking structured datasets with user-friendly interfaces, the tool transforms static knowledge into actionable insights, aligned with the vision of an interconnected ecosystem of digital twins.

Impact and Alignment with Digital Innovation Principles

The AI tool developed demonstrates AstraZeneca’s commitment to the principles of speed, sustainability, and cost-effectiveness, as detailed in our previous work. These advancements are a practical realization of the central thesis of our research: that mechanistic understanding, hybrid modeling, and AI-powered digital tools are foundational to the future of pharmaceutical development.

Through the LSPD project, we have not only streamlined biologics manufacturing but also redefined knowledge accessibility, significantly reducing the reliance on manual efforts to locate and interpret critical information And reducing the reliance on development SMEs as well as reducing travel for SME troubleshooting. Furthermore, the project serves as a compelling example of the foundational benefits

achieved through the comprehensive upskilling program implemented across our organization. As discussed in our LMDE 2023 paper, successful AI adoption extends beyond technological advancements—it necessitates a cultural and organizational shift towards embracing a digital mindset. This mindset is built on a framework of digital innovation that prioritizes adaptability, continuous learning, and viewing digital technologies as integral to strategic business operations rather than as auxiliary tools.

AstraZeneca's Pharmaceutical Technology & Development (PT&D) function has made remarkable progress in late 2023 and in 2024 in cultivating this mindset, with a deliberate emphasis on embedding AI capabilities deeply across teams and processes. A cornerstone of this transformation has been our AI Ambassador program, a bottom-up initiative designed to empower employees at all levels to harness the potential of AI. This program, combined with leadership training in AI, has been instrumental in fostering the skills and confidence necessary to drive the impactful results presented in this paper. By enabling individuals to embrace and apply AI technologies effectively, this initiative has proven to be a catalyst for A Digital Innovation Framework with innovations and advancements that are now shaping our business moving forward.

OPTIMIZING ROBOTIC PICK-AND-PLACE OPERATIONS FOR RECONFIGURABLE MANUFACTURING SYSTEMS

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Keywords: Robotics in manufacturing, industrial and applied mathematics for production, optimization methods and simulation tools.

Reconfigurable Manufacturing Systems (RMS) (Koren et al., 1999) are designed to adapt to changing production requirements by dynamically adjusting their structure and functionality. This adaptability is crucial in modern manufacturing environments where flexibility and responsiveness to varying demands play a significant role in maintaining efficiency.

Pick and place operations are a fundamental part in assembly production systems, where robotic automation enhances efficiency, reducing errors, and optimizing production. Optimizing the picking sequence of semi-finished products and components becomes a major challenge. The goal is to determine the most efficient sequence for a robotic agent to collect items from specific locations, minimizing travel time.

In this study, we model the robotic pick and place process as a Bipartite Traveling Salesman Problem (BTSP), a variation of the classical Traveling Salesman Problem (TSP). The problem structure arises from the warehouse setup, where a robot must alternate between two disjoint sets of locations: the Gravity Rack (GR) set, which stores components categorized by type, and the Kit Holder (KH) set, where components are placed in designated kit holders before proceeding to the assembly stage. Each component type is stored separately within the GR, and each KH contains a unique combination of components based on assembly requirements, this structure sets the constraint that the robot does not visit two consecutive locations of the same type. The robotic picking and placing process aligns with RMS principles, as it requires the system to manage various configurations of KHs and GRs while optimizing picking sequences.

To solve this problem, we introduce and compare three optimization approaches: Heuristic Methods, the Linear Method, and the Exact Method. The heuristics methods, including Nearest Neighbor (NN) (Halim and Ismail, 2019) and 2-opt (Uddin et al., 2023), provide fast approximations of the optimal picking sequence. The Linear Method represents the industry-standard pick and place operation used in our case study where KHs are filled sequentially. The Exact Method employs an Integer Programming (IP) model (Miller et al., 1960) to compute the optimal picking sequence, ensuring the lowest possible travel cost. The model was solved using the CBC (Coin-or Branch and Cut) solver, version 2.10.3 (Forrest et al., 2003). Our

evaluation demonstrates that the exact method consistently outperforms the linear method in terms of optimality, achieving a 5% to 20% improvement over baseline linear approach.

Beyond optimization, we introduce a simulation service designed to evaluate different GR configurations and their impact on system performance. Unlike the optimization service, which is used under a fixed GR layout, our simulation dynamically tests multiple setups by randomizing GR configurations and KH setup. The simulation structure allows users to generate multiple GR configurations and test their impact on performance, analyze the effect of different KH setups to determine the most effective setup, define and execute a specific number of randomized configurations, and identify the best-performing configuration, which is then compared against the baseline setup. The exact method is applied to evaluate the performance of each configuration systematically. The results from the simulation service reveal that optimized GR configurations can improve efficiency by 20% to 30% compared to the baseline linear method and 5% to 15% over the exact method. This highlights the importance of configuration flexibility in warehouse planning, as even an optimal picking sequence can be further enhanced by an improved layout.

To ensure scalability and adaptability, we developed a modular system that integrates both optimization and simulation services. The architecture is designed to handle diverse input configurations, allowing users to provide warehouse data in a structured JSON format specifying the picking method (Exact, Linear, or Heuristics), KH setups, GR positions, and the distance matrix.

It processes optimization tasks, calling the selected optimization algorithm, computing the picking sequence, and returning the results. The system enables real-time simulation testing, dynamically generating multiple GR configurations, evaluating their efficiency, and comparing performance metrics to support data-driven and decision-making.

To validate our approach, we conducted experiments under realistic warehouse conditions, evaluating both the optimization service and the simulation service across different scenarios. Our results demonstrate that exact optimization provides the best results. Nearest Neighbor and 2-opt heuristics offer fast approximations but can be significantly improved when combined with local search techniques. The linear method consistently underperforms compared to these approaches. The simulation service demonstrates that dynamically adjusting the GR configuration and KH setup can gain significant efficiency improvements.

While the optimization and simulation services provide significant advancements in robotic warehouse picking, several ports remain open for further exploration. The integration of Graph Neural Networks (GNNs) (Drori et al., 2020) presents a promising approach for learning and predicting efficient picking sequences by capturing spatial relationships in warehouse layouts. Reinforcement learning-based (Sutton, 2018) optimization could further improve decision-making over time based on historical data. The extension of our approach to multi-agent systems, where multiple robots collaborate to optimize warehouse operations, presents another area of interest.

This work presents a comprehensive approach to robotic warehouse picking optimization by integrating Bipartite TSP-based optimization with a flexible simulation

service. Our findings demonstrate that the exact method delivers better results. The simulation service enhances decision-making by exploring alternative layouts and configurations, revealing that structural modifications alone can lead to performance gains. By combining optimization techniques and simulation, our system offers a scalable, efficient, and adaptable solution for modern robotic warehouse automation. These contributions set the way for future advancements in intelligent warehouse management, particularly through machine learning-driven approaches and real-time adaptability.

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References

- Drori, I. et al. (2020). Learning to solve combinatorial optimization problems on real-world graphs in linear time. In 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA). IEEE.
- Sutton, R.S. (2018). Reinforcement learning: An introduction. A Bradford Book.
- Miller, C.E., Tucker, A.W., and Zemlin, R.A. (1960). Integer programming formulation of traveling salesman problems. *Journal of the ACM (JACM)*, 7(4), 326–329.
- Uddin, F., Riaz, N., Manan, A., Mahmood, I., Song, O.Y., Malik, A.J., and Abbasi, A.A. (2023). An improvement to the 2-opt heuristic algorithm for approximation of optimal tsp tour. *Applied Sciences*, 13(12), 7339.
- Forrest, J. et al. (2003). CBC (Coin-or branch and cut). Coin-or Foundation. Available from: <https://github.com/coin-or/Cbc>.
- Halim, A.H. and Ismail, I. (2019). Combinatorial optimization: comparison of heuristic algorithms in travelling salesman problem. *Archives of Computational Methods in Engineering*, 26, 367–380.
- Koren, Y., Heisel, U., Jovane, F., Moriwaki, T., Pritschow, G., Ulsoy, G., Van Brussel, H. (1999). Reconfigurable manufacturing systems. *CIRP Annals* 48(2), 527–540.
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ENABLING TECHNOLOGIES FOR RECONFIGURABLE MANUFACTURING SYSTEMS AND THEIR IMPACT ON BUSINESS MODELS

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Keywords: Modularity, reconfigurable manufacturing, digital transformation.

Introduction

The manufacturing sector is undergoing a rapid transformation triggered by evolving customer expectations, increased competition, data availability, technological advances, and a volatile business environment (Jones, Hutcheson, and Camba 2021). This transformation concerns business processes, customer experience, the business model, and the whole organization (Doukidis, Spinellis, and Ebert 2020; Farmakis et al. 2024B). Companies have initiated a change process by adopting innovative technologies, systems, and key organizational capabilities to allow key economic, capability, and innovation-driven outcomes (Gong and Ribiere 2021) in the process of Digital Transformation.

The Reconfigurable Manufacturing Systems (RMS) are at the center of this transformation as companies adjust to the volatile and evolving business environment (Arnarson et al. 2023). RMS allows companies to meet customers' needs and achieve mass customization and personalization strategies (Campos Sabioni, Daaboul, and Le Duigou 2022). Reconfigurable Manufacturing Systems exhibit several distinctive characteristics, including modularity, integrability, customization, convertibility, and diagnosability (Bortolini, Galizia, and Mora 2018). Developing and implementing a range of key, interconnected technologies and systems is essential to realizing these attributes. Digital twins are one of the core technologies that provide the basis for incorporating additional services, such as optimization and analytics, or other technologies, such as AI, that can be exploited (Zhang et al. 2019).

Nevertheless, despite the great potential of such systems, manufacturing firms struggle to implement them effectively in practice, and the adoption of RMS is low (Andersen et al. 2024). Most academic literature is concentrated on the technical development of RMS-enabling technologies, providing little evidence on how they can be integrated into the organization and clarifying the business value and the effect they have on the business model elements of manufacturing firms. Literature suggests that, in general, Industry 4.0 technologies, including digital twins and AI, impact companies' business models on value offer, value creation, and value capture dimensions in manufacturing (Baloutsos, Karagiannaki, and Mourtos 2020; Farmakis et al. 2024A). Hence, more research is needed to show how RMS-enabling technologies can support innovation across those three dimensions. The following research question has been formulated.

Research Question: How can enabling technologies for Reconfigurable Manufacturing Systems drive innovation across the elements of manufacturing business models, including value offer, value creation, and value capture?

Research Approach

A multiple case study methodology was adopted to explore the diverse implications of reconfigurability-enabling technologies across industrial cases (Eisenhardt, 1989). Those cases concern an advanced system based on digital twins as well as relevant supporting technologies such as AI applications, optimization, simulation, and analytics to enable modularity in production, which has been developing in the context of the MODAPTO project for the last few years (Farmakis et al. 2025). We purposely chose these cases due to their relevance to our research question, the data availability, and the diversity of industries.

Our research follows an exploratory and qualitative approach to gain insights relevant to our research question. For this study, we exploit information from various sources, such as workshop data, structured questionnaires with end users and technology providers, and on-site observations and reports. Each case will be analyzed independently, followed by cross-case synthesis to identify variations.

- **Case 1** integrates industrial digital twins to enhance robotic systems with energy optimization, sustainability analytics, and interoperability, enabling precise energy and carbon calculations and efficiency in modular robot designs.
- **Case 2** concerns the development of modular, reconfigurable production lines, optimizing processes with simulations, predictive maintenance, and efficient scheduling, transforming the shopfloor from a sequential production facility to a production facility consisting of different production modules.
- **Case 3** refers to the automated kitting in automotive assembly with intelligent containers, optimizing just-in-time delivery and enhancing logistics and assembly efficiency by utilizing novel modular kit holders that can be adjusted to the respective content.

The proposed research consists of three phases:

- **Phase #1:** An industry-wide questionnaire based on the adapted constructs of (Maganha, Silva, and Ferreira 2019) to identify different manufacturing organizations that are similar to the research cases and the degree to which they can undertake a Digital Transformation for re-manufacturing (at a production or product level).
- **Phase #2** includes the execution of the Digital Transformation of the three cases as well as a set of structured interviews to examine the expected and observed outcomes of the modular transformation efforts of the factories.
- **Phase #3** includes examining the outcome of the modular transformation in terms of the new business models that are thus enabled.

The research draws on strategic management and lean startup tools to conceptualize and present BM, such as the Value Proposition Canvas and the Business Model Canvas (BMC) framework (Osterwalder and Pigneur 2010). It follows a similar approach to Baloutsos, Karagiannaki, and Mourtos 2020. BMs can be categorized into

nine interconnected components: value propositions, customer segments, channels, customer relationships, revenue streams, key resources, key activities, key partnerships, and cost structures. BMC provides a structured approach to enable us to understand how the enabling technologies implemented in the cases can, on the one side, enhance the BMs of firms that adopt them, and on the other side, the new BMs can be adopted from technology providers to scale up activities.

Expected Results

The expected results of this study are multifaceted, aiming to provide theoretical insights and practical applications by leveraging and connecting findings with empirical data from real-world industrial case studies. A previous study that examined the same cases suggested that digital twins, AI applications, simulation, optimization, predictive maintenance, production design, and reconfiguration can provide core functionalities that alleviate the pains of manufacturing companies. These technologies offer significant value propositions, facilitating process transformation, customer experience, and business models (Farmakis et al. 2025). This study aims to expand on previous research by exploring how these technologies will enhance the business models of manufacturing firms from a user perspective and how they enable the creation of new business models from the perspective of technology providers and manufacturers, as well as shedding light on the remaining industries' potential for remanufacturing.

The core idea of this study is to examine how various elements of business models are influenced by enabling technologies, such as digital twins, simulation, optimization, predictive maintenance, and production design and reconfiguration. The research aims to:

- Give industrial stakeholders actionable insights to craft effective industrial strategies
- Explore how technology providers can adopt innovative business models to make these technologies more accessible and viable in the market
- Identify scalable and feasible approaches, such as subscription models, pay-as-you-go services, or co-creation partnerships, to address the specific needs of small and medium-sized enterprises (SMEs)
- Develop business models supporting SMEs' adoption of Industry 4.0 technologies
- Present the industrial business models of companies likely to adopt or offer these technologies as services
- Provide a practical framework to guide industrial strategies for their effective implementation
- Uncover new policy recommendations to assist decision-makers in supporting companies during the transition from Industry 4.0 to Industry 5.0

References

Andersen, Rasmus, Alessia Napoleone, Ann-Louise Andersen, Thomas Ditlev Brunoe, and Kjeld Nielsen. 2024. 'A Systematic Methodology for Changeable and Reconfigurable Manufacturing Systems Development'. *Journal of Manufacturing Systems* 74 (June):449-62. <https://doi.org/10.1016/j.jmsy.2024.04.008>.

Arnarson, Halldor, Hao Yu, Morten Olavsbråten, Bernt Bremdal, and Bjørn Solvang. 2023. 'Towards Smart Layout Design for a Reconfigurable Manufacturing System'. *Journal of Manufacturing Systems* 68 (May):354-67. <https://doi.org/10.1016/j.jmsy.2023.03.012>.

Baloutsos, Stratos, Angeliki Karagiannaki, and Ioannis Mourtos. 2020. 'Business Model Generation for Industry 4.0: A "Lean Startup" Approach'. *The International Technology Management Review* 9 (July). <https://doi.org/10.2991/itm.r.k.200630.001>.

Bortolini, Marco, Francesco Gabriele Galizia, and Cristina Mora. 2018. 'Reconfigurable Manufacturing Systems: Literature Review and Research Trend'. *Journal of Manufacturing Systems* 49 (October):93-106. <https://doi.org/10.1016/j.jmsy.2018.09.005>.

Campos Sabioni, Rachel, Joanna Daaboul, and Julien Le Duigou. 2022. 'Concurrent Optimisation of Modular Product and Reconfigurable Manufacturing System Configuration: A Customer-Oriented Offer for Mass Customisation'. *International Journal of Production Research* 60 (7): 2275-91. <https://doi.org/10.1080/00207543.2021.1886369>.

Doukidis, Georgios, Diomidis Spinellis, and Christof Ebert. 2020. 'Digital Transformation - A Primer for Practitioners'. *IEEE Software* 37 (5): 13-21. <https://doi.org/10.1109/MS.2020.2999969>.

Eisenhardt, Kathleen M. 1989. 'Building Theories from Case Study Research'. *Academy of Management Review* 14 (4): 532-50. <https://doi.org/10.5465/amr.1989.4308385>.

Farmakis, Timoleon, Stavros Lounis, Efstathios Plitsos, Giulio Vivo, Julien Mascolo, Olivier Jotz, and Tobias Hohmann. 2025. "Identifying the Value Proposition of Modular Manufacturing Information Systems for Digital Transformation." In *Advanced Perspectives and Trends in Digital Transformation of Firms*, edited by Francesco Schiavone, Nessrine Omrani, and Heger Gabteni. Proceedings of the 2nd International Conference of the Digital Transformation, 22-25 May, Napoli, Italy. (To be published by Springer)

Farmakis, Timoleon, Stavros Lounis, Ioanna Sofia Georgoutsou, Anastasios Koukopoulous, and Ioannis Mourtos. 2024A. 'Innovations in Manufacturing Business Models Enabled by Digital and AI-Driven Transformation: A Conceptual Framework'. In *2024 IEEE International Conference on Engineering, Technology, and Innovation (ICE/ITMC)*, 1-8. <https://doi.org/10.1109/ICE/ITMC61926.2024.10794358>.

Farmakis, Timoleon, Stavros Lounis, Ioannis Mourtos, and Georgios Doukidis. 2024B. 'Digital Twins as an Integral Part of Manufacturing Digital Transformation'. In *Leading and Managing in the Digital Era*, edited by Gregory Prastacos and Nancy Pouloudi, 173-87. Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-65782-5_12.

Gong, Cheng, and Vincent Ribiere. 2021. 'Developing a Unified Definition of Digital Transformation'. *Technovation* 102 (April):102217. <https://doi.org/10.1016/j.technovation.2020.102217>.

Jones, Matthew D., Scott Hutcheson, and Jorge D. Camba. 2021. 'Past, Present, and Future Barriers to Digital Transformation in Manufacturing: A Review'. *Journal of Manufacturing Systems* 60 (July):936-48. <https://doi.org/10.1016/j.jmsy.2021.03.006>.

Maganha, Isabela, Cristovão Silva, and Luís Miguel D. F. Ferreira. 2019. 'The Impact of Reconfigurability on the Operational Performance of Manufacturing Systems'. *Journal of Manufacturing Technology Management*, June. <https://doi.org/10.1108/JMTM-12-2018-0450>.

Osterwalder, Alexander, and Yves Pigneur. 2010. *Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers*. John Wiley & Sons.

Zhang, Chenyuan, Wenjun Xu, Jiayi Liu, Zhihao Liu, Zude Zhou, and Duc Truong Pham. 2019. 'A Reconfigurable Modeling Approach for Digital Twin-Based Manufacturing System'. *Procedia CIRP*, 11th CIRP Conference on Industrial Product-Service Systems, 83 (January):118-25. <https://doi.org/10.1016/j.procir.2019.03.141>.

ENERGY EFFICIENT ROBOTIC ARM MOTION OPTIMIZATION VIA DIGITAL TWINS

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Keywords: Robotics in manufacturing, optimization and control, industrial and applied mathematics for production.

Energy efficiency in industrial robotics is a critical factor in optimizing manufacturing processes, reducing operational costs, and minimizing environmental impact (Akundi et al. (2022)). Robotic systems are used to perform a wide range of tasks, such as welding, hemming, etc. Traditional robot programming approaches often rely on the experience of human programmers to determine movement parameters, leading to suboptimal energy consumption. In this paper, the operation of a robotic arm mounted with a roller hemming head is examined. We propose a novel Digital Twin (DT)-based optimization framework that systematically explores the energy-time trade-offs of robotic movements and minimizes total energy consumption while respecting operational constraints. Digital twins can enable robotic systems with simulation and optimization capabilities. Liu et al. (2022) enhanced mobile robot trajectory optimization by utilizing DTs, conducting training in virtual environments, and employing genetic algorithms to reduce errors in real-world operations. Our approach integrates an Integer Programming (IP) model with a preprocessing method based on Pareto dominance, ensuring computational feasibility without compromising solution quality.

The optimization process begins by generating multiple operational scenarios for each robotic movement within a production cycle. These scenarios, produced by the DT of the robot, represent different movement configurations defined by parameters such as velocity, acceleration, trajectory type, and axis positions. Two primary movement types are considered: linear movements, which ensure precise path control, and point-to-point (PTP) movements, which prioritize time efficiency over trajectory accuracy. Each scenario is characterized by its corresponding energy consumption and task completion time. The approach of breaking down a problem into a discrete set of alternatives to aid decision-making in real-world scenarios has been previously explored in the literature. For instance, Galán-Martín et al. (2016) employed Data Envelopment Analysis (DEA) to assess sustainable options within a system by evaluating economic, environmental, and social indicators. The extensive scenario generation process enables a comprehensive exploration of the potential trade-offs between speed and energy efficiency.

Given the large number of generated scenarios, solving the optimization problem directly becomes computationally infeasible for large-scale instances. To address this challenge, we introduce a preprocessing technique that applies Pareto filtering to eliminate strictly dominated scenarios before solving the IP model. A scenario is considered Pareto-dominated if another scenario exists that performs at least as

well across all criteria and strictly better in at least one. By retaining only Pareto-optimal scenarios, we significantly reduce the problem size while ensuring that the solution obtained from the filtered set remains optimal in terms of total energy consumption.

To implement our methodology, we develop an optimization service that seamlessly integrates into the robotic cell design phase. This service retrieves the existing robot program, extracts movement information, and generates corresponding operational scenarios using DT simulation. The Pareto filtering method is then applied to remove suboptimal scenarios before solving the refined IP model, which determines the optimal movement sequence that minimizes total energy consumption while meeting production constraints, such as given cycle time requirements. The optimized parameters are subsequently used to generate a new robot program, ensuring that the final motion plan achieves maximum energy efficiency without degrading performance.

We evaluate the performance of our proposed approach through extensive computational experiments, comparing the solution times and scalability of two methods: (i) solving the IP model without filtering and (ii) applying Pareto filtering before solving the IP model. Our experiments systematically vary the number of operational scenarios per movement, ranging from 1,000 to 10 million, to assess the impact of filtering on computational efficiency. The results demonstrate that solving the IP model directly becomes infeasible for large-scale instances (beyond 5 million scenarios per movement), whereas our Pareto filtering method significantly reduces solution times. For example, in problems with 1,000,000 scenarios per movement, solving the IP model without filtering requires 357.113 seconds on average, whereas with Pareto filtering, the total execution time (including both filtering and optimization) is substantially lower, at 0.557 seconds.

A key advantage of our approach is its ability to enhance the tractability of energy optimization problems in robotic programming. By reducing the scenario set to a manageable size, we enable the optimization of complex robotic movement sequences that would otherwise be computationally prohibitive. Our results confirm that Pareto filtering acts as an effective preprocessing step, allowing for large-scale optimization while maintaining high solution quality. The reduction in computational complexity makes it feasible to apply this method in industrial settings where rapid optimization is required for dynamic production environments.

Our approach is particularly relevant for robotic applications that require energy-efficient motion planning, such as automotive manufacturing, assembly lines, and other industrial automation settings. The methodology is currently implemented for roller hemming robots, where movement efficiency is a primary concern. However, the principles of our approach are broadly applicable to other robotic systems, including those equipped with energy-intensive tools such as spot welding guns. Extending the methodology to include tool-specific energy consumption models is a promising avenue for future research, as it will allow for the simultaneous optimization of both movement and tool operation.

Additionally, future work may explore the integration of machine learning techniques to further enhance the scenario generation process. By leveraging predictive models trained on historical robot performance data, it may be possible to refine the

selection of initial scenarios before Pareto filtering, further improving computational efficiency.

Our study provides a robust foundation for energy-efficient robotic programming, demonstrating how DT simulation, Pareto dominance, and Integer Programming can be effectively combined to achieve substantial computational savings. The proposed methodology enables manufacturers to optimize robotic energy consumption at scale, improving both economic and environmental sustainability in modern production systems.

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References

- Akundi, A., Euresti, D., Luna, S., Ankobiah, W., Lopes, A., & Edinbarough, I. (2022). State of industry 5.0—analysis and identification of current research trends. **Applied System Innovation*, 5*(1), 27.
- Galán-Martín, Á., Guillén-Gosálbez, G., Stamford, L., & Azapagic, A. (2016). Enhanced data envelopment analysis for sustainability assessment: A novel methodology and application to electricity technologies. **Computers & Chemical Engineering*, 90*, 188–200.
- Liu, X., Jiang, D., Tao, B., Jiang, G., Sun, Y., Kong, J., Tong, X., Zhao, G., & Chen, B. (2022). Genetic algorithm-based trajectory optimization for digital twin robots. **Frontiers in Bioengineering and Biotechnology*, 9*, 793782.
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Session C4

AI-POWERED ENTREPRENEURSHIP: FROM KNOWLEDGE CREATION TO STRATEGIC IMPLEMENTATION

Chair: Konstantinos Fouskas, University of Macedonia, Greece

DIGITAL ENTREPRENEURSHIP AND ARTIFICIAL INTELLIGENCE: INVESTIGATING HOW AI IS SHAPING DIGITAL ENTREPRENEURSHIP

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Keywords: Artificial Intelligence, digital entrepreneurship, AI-driven startups.

The evolution of technology in recent years has brought about many changes in the economy and business sector. Especially in the last decades, technological developments have been rapid. The Fourth Industrial Revolution, as it is called, has transformed all aspects of business (Mathew et al., 2023). Entrepreneurship that utilizes these technological developments is called digital entrepreneurship (Liu et al., 2023), expanding the use of technologies at any stage of the business from creation to product distribution, marketing and daily operations (Steininger, 2018).

One of the most significant technological changes of recent years, which is part of the Fourth Industrial Revolution (Mathew et al., 2023) is Artificial Intelligence, which has the potential to transform the operation of digital businesses in terms of business models, strategies and processes they use (Upadhyay et al., 2021). The scientific community fully accepts AI as a revolutionary technology capable of shaping the field of entrepreneurship and opening new perspectives. There are many areas where AI can be used, but the most prominent ones include healthcare, media, technology, education, logistics, travel and e-commerce. (Mathew et al., 2023). By leveraging AI, young entrepreneurs can gain a competitive advantage as it has a multitude of applications. Decision-making, strategy formulation, data collection and market analysis are some of these applications which result in increasing the efficiency of a business (Duong, 2024).

Artificial intelligence can simulate human speech and behavior; therefore, it cannot be limited to a specific application area (Righi et al., 2020). For this reason, AI-related technologies can be categorized according to the characteristics that distinguish them from other technologies. This categorization includes eight main areas in which the use of AI can be categorized. These are reasoning through logic, design, learning, communication, perception, integration and interaction, services and finally the ethics and philosophy of AI. These eight categories are divided into several subcategories such as machine learning, audio and video processing, organization and programming, AI ethics, etc. (Samoili et al., 2020).

The use of AI has the potential to greatly influence the way a company operates in terms of its business model. Companies such as Airbnb, Uber and Amazon have integrated AI-driven technologies into their business models to become more competitive (Mishra & Tripathi, 2021). The main change it can bring about is in terms of the internal processes of the business which are automated using AI. Processes that are repetitive and do not require any specialization can be carried out by AI, thus enabling employees to work on more productive tasks. In addition, AI enables companies to create new services and products (Widayanti & Meria, 2023). Extracted data, such as consumer preferences and habits, can be easily analyzed by AI systems, making surveys conducted by marketing departments easier, faster and

more reliable. These surveys can be used to analyze consumers so that marketing campaigns can be better targeted. (Rivas and Zhao, 2023). Such data can be extracted from social networking platforms and processed by artificial intelligence systems to result in products that will be accepted by customers (Ozcan et al., 2021). The integration of AI in the creation of a product can identify new opportunities for product development (Mariani et al., 2023). In addition, when creating a product, the use of AI can help businesses reduce the time needed to create the new product (Hutchinson, 2021). Finally, the integration of artificial intelligence in businesses can help to make predictions regarding consumer demands, product specifications and the demand for the product or service (Mathew et al., 2023).

According to Perifanis & Kitsios (2023), the use of artificial intelligence by entrepreneurs can help companies develop all the necessary skills to adapt to market changes and gain an aggressive advantage over their competitors. In addition, business leaders can benefit from the use of AI to be flexible in shaping business strategy. Big data makes it possible for business management to make choices based on possible future situations.

In addition to the endless possibilities offered by the utility of AI in business, there are also moral factors to consider in its adoption. An AI tool, far from being trained on a set of facts, can provide biased solutions, with the result that a firm basing its selection on AI can also appear unfair in its decision. (Attard-Frost et al., 2022). It is therefore important for businesses to ensure that the information used by AI structures is representative of different social corporations. Since the outputs generated by artificial intelligence cannot always be traced back to the exact processes and standards used, AI systems should be regularly monitored under human supervision to prevent biased responses (Kasneci et al., 2023).

The existing literature focuses mainly on how AI is being adopted by companies that are already established. These companies are often large organizations that can invest technological and financial resources to remain competitive and utilize AI as a means of operational or strategic advantage. However, there is currently limited research in start-up companies which are smaller or in the early stages of development and funding. We understand that research on this topic can shed light on how AI can be integrated and utilized by pre-seed or seed-stage startups and reveal if it can become a transformative force that will allow them to scale with limited resources compared to established ones, or if it will widen the gap between them. We believe that these stages of a start-up are critical as entrepreneurs typically seek to develop their business models and their MVPs while seeking to raise revenue from various sources of funding. Our research aspires to fill the gap in the literature by contributing to the understanding of the challenges and opportunities for start-up businesses at this stage.

Some key issues that could be part of such a study include the technological, financial and organizational challenges that start-ups face at the pre-seeding and seeding stage compared to large organizations and if AI can help start-ups to grow efficiently with limited resources and develop their own MVPs. Another interesting aspect that can be explored is the impact that AI has on start-ups in terms of raising funding from capital investors and the conditions that allow start-ups to use AI to balance competition. Also, research can be conducted on whether there

are specific industries that encourage the adoption of AI at these early stages and how the founders of these companies can adapt their strategic planning accordingly. Finally, we consider that a future analysis of ecosystems would be useful in terms of the support they provide to start-ups using AI and the best practices they utilize. These research questions can help to extract valuable insights regarding how AI affects early-stage start-ups in order to better understand the rapidly changing entrepreneurial landscape.

The article will follow a data-driven methodology in order to provide empirical data on how AI shapes digital entrepreneurship particularly within startup ecosystems. Instead of following a more traditional research methodology of questionnaires or interviews, both structured and unstructured data will be used to provide empirical insights. The data used in the analysis will be the available data from the last five years as AI has evolved rapidly during this period. Furthermore, this will ensure that the analysis will be based on up-to-date data that reflect current developments. In addition, the research will focus on data mainly drawn from European countries as there are large differences compared to the US market. Finally, the survey data will be drawn for companies that are mainly active in the broader technology, media and telecommunications sectors as these sectors seem to have used AI the most in the past year. This will enhance the objectivity and reliability of the research while allowing for more accurate prediction of the funding trends that exist. The study will integrate information and data from various databases to ensure a comprehensive analysis such as Crunchbase and Statista. The data will be analyzed to identify patterns and correlations that answer the research questions in order to contribute to a deeper understanding of AI's role in the evolving startup landscape.

References

- Attard-Frost, B., De los Ríos, A. and R. Walters, D. (2022) 'The ethics of AI Business Practices: A review of 47 Ai Ethics Guidelines', SSRN Electronic Journal [Preprint]. doi:10.2139/ssrn.4034804.
- Duong, C.D. (2024) 'What makes for digital entrepreneurs? the role of AI-related drivers for nascent digital start-up activities', European Journal of Innovation Management [Preprint]. doi:10.1108/ejim-02-2024-0154.
- Hutchinson, P. (2021) 'Reinventing innovation management: The impact of self-innovating artificial intelligence', IEEE Transactions on Engineering Management, 68(2), pp. 628–639. doi:10.1109/tem.2020.2977222.
- Kasneci, E. et al. (2023) 'Chatgpt for good? on opportunities and challenges of large language models for Education', Learning and Individual Differences, 103, p. 102274. doi:10.1016/j.lindif.2023.102274.
- Liu, W. et al. (2023) 'Digital Entrepreneurship: Towards a Knowledge Management Perspective', Journal of Knowledge Management, 28(2), pp. 341–354. doi:10.1108/jkm-12-2022-0977.
- Mariani, M.M. et al. (2023) 'Artificial Intelligence in Innovation Research: A systematic review, Conceptual Framework, and Future Research Directions', Technovation, 122, p. 102623. doi:10.1016/j.technovation.2022.102623.
- Mathew, D., Brintha, N.C. and Jappes, J.T. (2023) 'Artificial Intelligence Powered Automation for Industry 4.0', Contributions to Environmental Sciences

& Innovative Business Technology, pp. 1–28. doi:10.1007/978-3-031-20443-2_1.

Mishra, S. and Tripathi, A.R. (2021) 'Ai Business Model: An Integrative Business Approach', *Journal of Innovation and Entrepreneurship*, 10(1). doi:10.1186/s13731-021-00157-5.

Ozcan, S. et al. (2021) 'Social Media Mining for ideation: Identification of Sustainable Solutions and opinions', *Technovation*, 107, p. 102322. doi:10.1016/j.technovation.2021.102322.

Perifanis, N.-A. and Kitsios, F. (2023) 'Investigating the influence of artificial intelligence on Business Value in the digital era of strategy: A literature review', *Information*, 14(2), p. 85. doi:10.3390/info14020085.

Righi, R. et al. (2020b) 'The AI techno-economic complex system: Worldwide landscape, thematic subdomains and technological collaborations', *Telecommunications Policy*, 44(6), p. 101943. doi:10.1016/j.telpol.2020.101943.

Rivas, P. and Zhao, L. (2023) 'Marketing with CHATGPT: Navigating the ethical terrain of GPT-based chatbot technology', *AI*, 4(2), pp. 375–384. doi:10.3390/ai4020019.

Samoili, S., Lopez Cobo, M., Gomez, E., De Prato, G., Martínez-Plumed, F., & Delipetrev, B. (2020) 'AI watch: defining artificial intelligence'. Towards an Operational Definition and Taxonomy of Artificial Intelligence. Available at: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC118163/jrc118163_ai_watch_defining_artificial_intelligence_1.pdf

Steininger, D.M. (2018) 'Linking Information Systems and Entrepreneurship: A Review and agenda for it-associated and Digital Entrepreneurship Research', *Information Systems Journal*, 29(2), pp. 363–407. doi:10.1111/isj.12206.

Upadhyay, N., Upadhyay, S. and Dwivedi, Y.K. (2021) 'Theorizing Artificial Intelligence Acceptance and Digital Entrepreneurship Model', *International Journal of Entrepreneurial Behavior & Research*, 28(5), pp. 1138–1166. doi:10.1108/ijeb-01-2021-0052.

Widayanti, R. and Meria, L. (2023) 'Business Modeling Innovation Using Artificial Intelligence Technology', *International Transactions on Education Technology (ITEE)*, 1(2), pp. 95–105. doi:10.34306/itee.v1i2.270.

REDEFINING KNOWLEDGE CREATION IN STARTUPS: THE ROLE OF AI

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Keywords: Knowledge creation, artificial intelligence (AI), entrepreneurship, prospecting, human-machine collaboration, nonaka, SECI model.

Abstract

This paper examines how early-stage entrepreneurs leverage artificial intelligence (AI) for knowledge creation, using Nonaka's SECI model as a framework. Drawing on in-depth interviews with six IT entrepreneurs in Cyprus, the study demonstrates that AI can support all four stages of the knowledge creation spiral (socialization, externalization, combination, and internalization), ultimately enabling entrepreneurs to prospect more effectively and develop new ventures. The findings suggest that AI can expand access to knowledge and expertise, accelerate the conversion of tacit to explicit knowledge, facilitate the combination of explicit knowledge from various sources, and support the internalization of explicit knowledge into actionable insights. However, the study also underscores the importance of human oversight, continuous learning, and recognizing that AI should augment, not replace, human capabilities in knowledge creation. The paper concludes by discussing the limitations of the study and outlining potential avenues for future research.

Introduction

The knowledge-based view (KBV) highlights how businesses use their knowledge assets to achieve and sustain a competitive advantage. While there has been extensive research on how established companies utilize knowledge management to enhance their competitiveness, the exploration of knowledge management in the area of entrepreneurship, where innovation is essential, remains limited (Bandera et al., 2017; Ameen et al., 2022). This is surprising, as effectively leveraging and managing knowledge can be critical for resource-constrained startups. For these ventures, the ability to create new knowledge is particularly crucial, as it fuels the innovation that drives their growth and survival. The integration of design thinking principles can further bolster the entrepreneurial process by promoting user-centricity and empathy, which are fundamental for comprehending market needs and generating innovative solutions (Sreenivasan & Suresh, 2024).

The objective of this research is to use the knowledge-based view as a conceptual frame to investigate how early-stage entrepreneurs use artificial intelligence (AI) to create and augment knowledge necessary for prospecting the business idea and their startup's early operations. Chalmers et al. (2021) suggest that "there is a need to understand how novel technological affordances will affect entrepreneurs and the myriad creative, cognitive, and physical processes enacted when launching a new venture." So far, little has been written specifically about the intersection between entrepreneurship and AI.

The rapid advancements in artificial intelligence (AI) represent a transformative "invention of a method of invention" that assists entrepreneurs in knowledge

management and innovation (Cockburn et al., 2018). AI's capacity to process vast amounts of data, identify patterns, and generate insights offers startups unprecedented opportunities to enhance their knowledge bases and streamline decision-making. Additionally, AI tools, such as chatbots, provide entrepreneurs with the ability to widen their knowledge beyond personal experience, offering encouragement and support through conversational affordances (Ramaul et al., 2024). By using AI in prospecting business ideas and integrating AI into their early operations, startups can overcome traditional barriers related to knowledge acquisition, dissemination, and utilization, thereby accelerating growth and competitiveness. However, it is important to stress that AI does not replace human creativity and decision-making; rather, it augments entrepreneurial efforts, enabling startups to navigate complex challenges and discover new market opportunities more effectively (Jarrahi, 2018; Ameen et al., 2022).

In this paper, we integrate insights from the knowledge-based view, specifically Nonaka's SECI model of knowledge creation, with the use of emerging AI technologies in the early stages of the entrepreneurial process. Considering that the intersection of AI and the KBV in entrepreneurial startups is still an emerging area of study, we use qualitative methodology based on interviews with entrepreneurs to gain a deeper insight into how AI can drive knowledge creation, support organizational learning, and contribute to sustainable competitive advantage.

Research methodology

To understand how entrepreneurs use AI to prospect their business ideas, we adopted a qualitative approach through in-depth interviews. Six accomplished IT entrepreneurs in Cyprus, with startups that have international audiences, agreed to share their experiences of utilizing AI at the early stages of prospecting, market exploration, and early stages of operation of their startups.

To protect entrepreneurs' identities, we will further refer to them as E1-E6. E1 is the founder of an educational learning game for children from 2-11 years old that sold more than two million copies on the App Store and Google Play, and an event calendar app advertising the cultural and educational activities on the island. E2 is the founder of a non-profit NGO dedicated to facilitating the entry of women into the tech sector. She is also a co-founder and a digital product designer in a SaaS (Software as a Service) company. E3 created an online platform that brings various service providers together with customers. The app can be purchased on the App Store and Google Play, and has recently become very popular in Cyprus. E4 is a Solutions Product Manager of an IT company that provides B2B solutions for project management. Having discovered a niche in the market, he started his own company to provide corporate clients with more custom-made solutions using AI. E5 is a founder of two startups: the first is a crypto-fintech service with an audience of one million people, and the second one is a startup in the real estate sector that automates finding, buying, and selling properties in Cyprus, two more EU countries and two Asian countries. E6 is the founder of the online market that sells solar-powered products through Amazon to the US market and through its own e-commerce shop in other countries. All the interviewed entrepreneurs have experience in the IT sector, have created digital products, and have experience using AI

and integrating AI into their business models.

Main findings

The findings demonstrate that AI tools can support all four stages of the knowledge creation spiral, enabling entrepreneurs to prospect more effectively and develop new ventures by leveraging both tacit and explicit knowledge. The insights gleaned from interviews with IT entrepreneurs in Cyprus suggest that AI can: a) expand access to knowledge and expertise, connect entrepreneurs with valuable contacts, simulate conversations, and expose them to diverse scenarios and market conditions outside of their experiential base; b) accelerate the conversion of tacit to explicit knowledge: help creating marketing materials, writing business plans, and generating prototypes; c) facilitate the combination of explicit knowledge from various sources: synthesizing data from market research, customer reviews, and analytics to gain new insights; d) support the internalization of explicit knowledge: translating formal knowledge into actionable insights, instructions, and operational procedures for employees. The study provides examples of how AI is utilized by entrepreneurs at all four stages of knowledge creation, as well as how the dynamic interaction between different modes takes place. The findings also highlight the importance of human oversight, continuous learning, and the recognition that AI cannot fully replace human expertise. AI should be viewed as a tool to augment, not replace, human capabilities in knowledge creation.

Limitations

This study has several limitations that should be considered when interpreting the findings. Firstly, the study is based on interviews with six IT entrepreneurs in Cyprus. The small sample size limits the generalizability of the findings. Secondly, the study focused specifically on entrepreneurs in the IT sector. It proved challenging to find entrepreneurs in other industries that have sufficient experience with AI and knowledge creation. This is in line with Chalmer et al. (2021) argument that AI remains a highly technical domain. Because of that, there is a misalignment between what many nascent entrepreneurs think they can do with the technology and what ultimately proves possible. While our sample selection allowed us to inquire into different uses of various AI technologies in the early entrepreneurial process, we acknowledge that the experiences of entrepreneurs in other industries may differ. Thirdly, the study was conducted in Cyprus, a small island nation. While five of our interviewees had startups with international audiences, the findings may be only partially transferable to other countries or regions.

Future research

Future research could further explore the intersection of AI and knowledge creation in entrepreneurship in the following ways: Following Nonaka's SECI model of knowledge creation, we assumed that tacit knowledge, though not entirely but at least to some extent, can be observed, learned, articulated, and converted to explicit knowledge. This approach, however, ignores the "essential inarticulability of tacit knowledge", reducing it to "what can be articulated" (Tsoukas, 2005). Nonaka's assumption might be counterproductive, as instead of attempting to convert

tacit knowledge, researchers should concentrate on drawing attention to things and constructive dialogue (Tsoukas, 2009). Exploring in which ways AI could facilitate constructive dialogue between entrepreneurs and even "participate" in a dialogue as a knowledge partner is a promising research area.

The paper explored how AI technologies can assist entrepreneurs and complement them in knowledge creation at the early stages of prospecting. This is because AI technology is still at an early stage of development and produces poor-quality output. As AI tools become more intelligent and more sophisticated, some tasks could likely be automated, and in some areas, human actions could be successfully substituted by machines. Future research could consider the ethical implications of their use, particularly concerning biases, and explore the long-term implications on entrepreneurship and innovation.

References

- Ameen, N., Sharma, G.D., Tarba, S., Rao, A., & Chopra, R. (2022). Toward advancing theory on creativity in marketing and artificial intelligence. *Psychology & Marketing*, 39, 1802–1825. <https://doi.org/10.1002/mar.21699>
- Bandera, C., Keshtkar, F., Bartolacci, M. R., Neerudu, S., & Passerini, K. (2017). Knowledge management and the entrepreneur: Insights from Ikujiro Nonaka's Dynamic Knowledge Creation model (SECI). *International Journal of Innovation Studies*, 1(3), 163-174.
- Chalmers, D., MacKenzie, N. G., & Carter, S. (2021). Artificial intelligence and entrepreneurship: Implications for venture creation in the fourth industrial revolution. *Entrepreneurship Theory and Practice*, 45(5), 1028-1053.
- Cockburn, I. M., Henderson, R., & Stern, S. (2018). The Impact of Artificial Intelligence on Innovation. NBER Working Paper No. 24449.
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.
- Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science*, 5(1), 14–37.
- Nonaka, I., & Von Krogh, G. (2009). Perspective—Tacit knowledge and knowledge conversion: Controversy and advancement in organizational knowledge creation theory. *Organization Science*, 20(3), 635-652.
- Ramaul, L., Ritala, P., & Ruokonen, M. (2024). Creational and conversational AI affordances: How the new breed of chatbots are revolutionizing the knowledge industries. *Business Horizons*.
- Sreenivasan, A., & Suresh, M. (2024). Design Thinking and Artificial Intelligence: A Systematic Literature Review Exploring Synergies. *International Journal of Innovation Studies*, 8, 297–312. <https://doi.org/10.1016/j.ijis.2024.05.001>
- Tsoukas, H. (2005). Do we really understand tacit knowledge? *Managing knowledge: An essential reader*, pp. 107, 1–18.
- Tsoukas, H. (2009). A dialogical approach to the creation of new knowledge in organizations. *Organization Science*, 20(6), 941–957.

STRATEGIC LAYOUT OF ENTERPRISE GENERATIVE ARTIFICIAL INTELLIGENCE TECHNOLOGY—EVIDENCE BASED ON PATENT DATA

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Keywords: Generative artificial intelligence, patent data, enterprise technology layout, large language model.

Generative Artificial Intelligence (GAI) has become one of the most hotly competitive fields in the new round of science and technology competition. Represented by Large Language Model (LLM), GAI has changed the traditional information production mechanism, and has shown great application prospects in finance (Li et al., 2023), education (Adeshola and Adepoju, 2024), medicine (Tan et al., 2024) and other fields. The current wave of technological development, represented by GAI, is affecting existing business operation models. For enterprises in this context, understanding the technology layout around GAI is critical to adjusting their operational strategies, addressing competitive risks, and planning for technology development.

Patents are an important way for enterprises to protect their intellectual property, and the information contained in patent data can be used for technology strategic planning (Ernst, 2003). Patent data has been used to analyse enterprises' strategic planning for emerging technologies (Kay et al., 2014), and there are also study have attempted to identify enterprises' competitors and collaborators based on patent data (Chang, 2012). In addition, with the development of artificial intelligence, researchers have paid more attention to related patents in recent years. Some researches have attempted to analyse the impact of artificial intelligence on productivity growth (Parteka & Kordalska, 2023) and industry chain (Zhao et al., 2024) based on patent data. Considering that there are fewer studies focusing on GAI patents and analysing the technology layout from the perspective of enterprises, this research attempts to explore the technology layout of Chinese enterprises in GAI technologies, utilizing Chinese patent data and employing a combination of analytical methods such as time series analysis, complex network, and large language model.

In this study, the representative technology of GAI is selected as the research object. In terms of data, using "large language model" as the keyword, a total of 9,647 relevant patent records from 2022 to 2024 were retrieved from the China National Knowledge Infrastructure (CNKI) patent database. Among these, 7,557 patents listed enterprises as applicants, accounting for approximately 78.3% of the total. The specific research is conducted from four perspectives: research and development heat change, enterprise cooperation mode, technology correlation and application potential. The details are as follows.

1. Research and development heat change: Over the three-year period, the number of patents related to LLM has increased year by year, with a significant surge in 2024 (8,440 patents). Among the top ten applicants by the number of patents, seven are enterprises. Combined with the aforementioned data, it is evident that enterprises are one of the key drivers in the development of LLM.
2. Enterprise cooperation mode: Among patents involving enterprises, independent research and development by enterprises dominate (88.3%), followed by collaboration between enterprises (8.8%), while partnerships with non-enterprise entities account for the smallest proportion, at only 2.8%.
3. Technology correlation: Based on the co-occurrence of patent classification codes, a co-occurrence network of enterprise patent classification codes was constructed. Community detection and node importance identification were then used on this network. Among the co-occurrence networks, the representative classification codes of the six largest communities are shown in Table 1. Based on Table 1, it can be concluded that the current focus of enterprise patent development about LLM can be summarized as network model, reasoning and semantic analysis, data preprocessing, multimodal data analysis, machine learning, and combined network.

No.	Classification Code	Meaning
1	G06N3/0455	Autoencoder Network; Encoder-Decoder Network
	G06N3/0464	Convolutional Network
	G06V10/82	Neural Network Application
	G06N3/08	Learning Method
2	G06F40/30	Semantic Analysis
	G06N5/04	Reasoning Methods or Device
	G06F16/332	Query Formulation
3	G06F18/25	Fusion Technology
	G06F18/22	Matching Criteria
	G06N3/084	Backpropagation
4	G10L15/26	Speech-to-Text Recognition System
	H04N21/44	Processing of Video Elementary Stream
5	G06N20/00	Machine Learning
6	G06N3/045	Combined Networks

Table 1: Classification Codes and Their Meanings

4. Application potential: Employing the GLM4-Plus model, we designed prompt statement to determine the most applicable industry for each patent based on its title. The results of the experiment show that in addition to the artificial intelligence industry, the current patent layout of enterprises around LLM also shows a large potential for application in industries such as finance, education, medical treatment, manufacturing and entertainment.

References

Adeshola, I., and Adepoju, A. P. (2024). “The opportunities and challenges of ChatGPT in education,” *Interactive Learning Environments*, 32(10), 6159-6172.

Chang, S. B. (2012). “Using patent analysis to establish technological position: Two different strategic approaches,” *Technological Forecasting and Social Change*, 79(1), 3–15.

Ernst, H. (2003). “Patent information for strategic technology management,” *World Patent Information*, 25(3), 233–242.

Kay, L., Youtie, J., & Shapira, P. (2014). “Signs of things to come? What patent submissions by small and medium-sized enterprises say about corporate strategies in emerging technologies,” *Technological Forecasting and Social Change*, 85, 17–25.

Li, Y., Wang, S., Ding, H., & Chen, H. (2023). “Large Language Models in Finance: A Survey,” *Proceedings of the Fourth ACM International Conference on AI in Finance*, 374–382.

Parteka, A., & Kordalska, A. (2023). “Artificial intelligence and productivity: Global evidence from AI patent and bibliometric data,” *Technovation*, 125, 102764.

Tan, S., Xin, X., & Wu, D. (2024). “ChatGPT in medicine: Prospects and challenges: a review article,” *International Journal of Surgery*, 110(6), 3701.

Zhao, X., Wu, W., & Wu, D. (2024). “How does AI perform in industry chain? A patent claims analysis approach,” *Technology in Society*, 79, 102720.

DIGITAL MARKETING FRAMEWORKS FOR STARTUPS: A COMPARATIVE REVIEW OF MODELS AND GAPS

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Keywords: Technology marketing, digital marketing, startup marketing, growth hacking, marketing optimization, digital marketing strategy.

Introduction

In the contemporary business landscape, characterized by rapid technological advancements and shifting consumer behaviors, startups implement digital tools to gain competitive advantage and achieve growth. Digital transformation allows startups to scale and use digital marketing techniques such as growth hacking, search engine optimization, and viral marketing (Andrade 2020; Bargoni et al. 2023). AI-driven analytics and chatbots improve conversion rates by providing personalized user experience (Patel 2020). Digital marketing enables startups to establish a brand presence, improve engagement with clients and optimize growth (Rizvanović et al. 2023). Moreover, startups implement digital strategies to innovate business models and improve their value propositions (Ghezzi and Cavallo 2020). Data analytics facilitate better decision-making, allowing startups to adapt quickly to market shifts (Dsouza and Panakaje 2023). This adaptability is critical for sustainability and investors, as a strong online presence attracts funding (Burton 2024; Moradi 2024). Social media marketing, for instance, not only fosters customer engagement but also enhances brand visibility, which is crucial for securing venture capital (Jin, Wu, and Hitt 2017; Nigam, Benetti, and Johan 2020). Since startups with their unique characteristics, typically operate under conditions of high uncertainty, limited resources, and an evolving market landscape, they need more agile and innovative approaches to marketing. Therefore, they require distinct marketing frameworks compared to established businesses. Given the diverse range of existing frameworks, selecting the right one is critical for aligning marketing efforts with business objectives. In this research, we compare various digital marketing frameworks, evaluating their effectiveness in the startup context.

Methodology

This study begins with a literature review to identify existing digital marketing frameworks. We choose to include 16 digital marketing frameworks, based on criteria focused on relevance and application in startup contexts. Additionally, interviews with 20 digital marketers from Greek startups were conducted using a semi-structured format to explore the characteristics of these frameworks and their practical applicability in their startups. Participants were selected in a way to represent different industry sectors.

Digital marketing frameworks in startup context

Several existing frameworks guide digital marketing efforts (Krabokoukis 2025). For example, the AARRR (Acquisition, Activation, Retention, Revenue, Referral)

framework prioritizes growth by focusing on optimizing the customer journey after acquisition (Zhang 2021). Similarly, the RACE (Reach, Act, Convert, Engage) framework provides a structured approach to attracting, engaging, and converting customers (Chaffey and Smith 2013). While it covers various aspects of digital marketing, it primarily deals with engagement and conversion. Additionally, the Bullseye Framework assists startups in identifying the most effective marketing channels to reach their target customers through experimentation (Weinberg and Mares 2015).

Framework Name	Key Elements	Best Suitable for Stage(s)
Customer Journey Mapping	Touchpoints, Pain Points, Experience	Early, Growth (Helps refine user experience)
Marketing Funnel	Awareness, Interest, Decision, Action	Early (Lead conversion focus)
Flywheel Model	Retention, Referrals, Engagement	Growth, Maturity (Customer retention & advocacy)
STP Model	Segmentation, Targeting, Positioning	Early, Growth (Market positioning)
7 Ps Marketing Model	Product, Price, Place, Promotion, People, Process, Evidence	Growth, Maturity (Broad marketing strategy)
The Hook Model	Trigger, Action, Reward, Investment	Early (User engagement & habit formation)
RACE Planning	Reach, Act, Convert, Engage	Growth (Comprehensive digital marketing planning)
AARRR (Pirate Metrics)	Acquisition, Activation, Retention, Referral, Revenue	Early (Growth hacking for traction)
Forrester's 5 Is	Involvement, Interaction, Immersion, Integration, Influence	Growth (Customer engagement focus)
Lean Analytics Stage Framework	KPIs, Iteration, Data, PMF Validation	Early (Data-driven decision-making)
Bullseye Framework	Channel Testing, Prioritization, Optimization	Early (Finding the best marketing channels)
Inbound Marketing Methodology	Content, SEO, Social, Nurturing	Early, Growth (Content-driven organic growth)
Growth Marketing Loop	Experimentation, Feedback, Iteration	Early, Growth (Continuous optimization)
SOSTAC Framework	Situation, Objectives, Strategy, Tactics, Action, Control	Growth, Maturity (Strategic planning)

Framework Name	Key Elements	Best Suitable for Stage(s)
STDC Model	See, Think, Do, Care	Early (Customer decision-making process)
PESO Model	Paid, Earned, Shared, Owned	Growth, Maturity (Integrated media strategy)

Table 1: Marketing Frameworks and Their Applicability

Key findings

Our analysis across various digital marketing frameworks shows that while many models provide robust strategies for targeting and engagement, they differ in their influence across several startup dimensions.

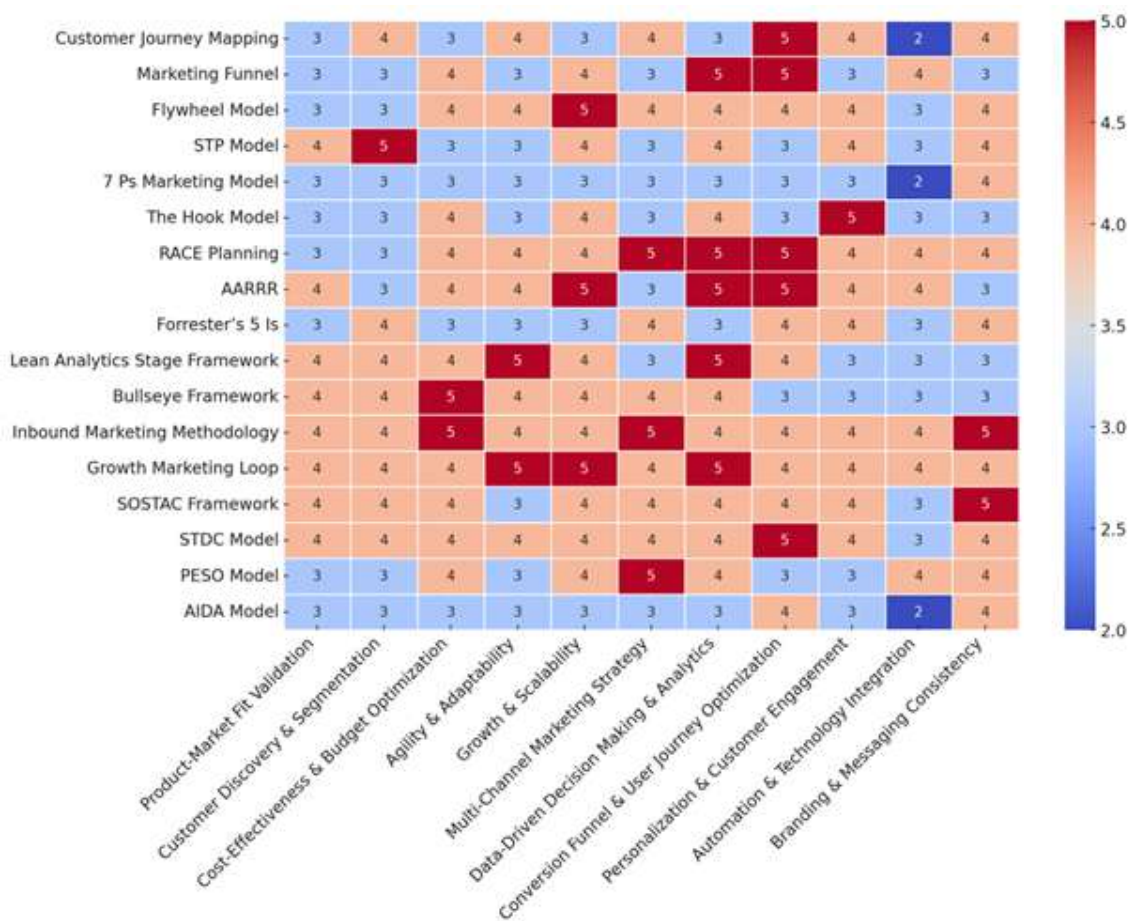


Figure 1: Comparison of key dimensions across marketing frameworks

Figure 1 reveals that certain digital marketing frameworks align with specific key dimensions, scoring the highest rating (5 - Excellent). Customer Journey Mapping, Marketing Funnel, RACE Planning, AARRR and STDC Model stand out in Conversion Funnel & User Journey Optimization, highlighting their strength in guiding customers through structured decision-making processes. Marketing Funnel, RACE,

AARRR, Lean Analytics Stage Framework and Growth Marketing Loop excel in Data-Driven Decision Making & Analytics, emphasizing their reliance on measurable insights for marketing effectiveness. STP Model scores highest in Customer Discovery & Segmentation, reinforcing its focus on precise audience targeting. Inbound Marketing and PESO Model lead in Multi-Channel Marketing Strategy, making them well-suited for omnichannel campaigns. Additionally, The Hook Model is the top performer in Personalization & Customer Engagement, underscoring its ability to drive user retention. Interestingly, Bullseye and Inbound Marketing rank highest in Cost-Effectiveness & Budget Optimization, showcasing their value for resource-efficient marketing strategies.

Identified gaps

Most digital marketing frameworks focus on growth and optimization, assuming that startups have already validated their audience. However, many startups, in the ideation or the early stages, struggle with product-market fit validation, often relying on a trial-and-error approach that can be costly and inefficient audience (Patil, Navalgund, and Mahantshetti 2022). There is an absence of an integrated approach dedicated to validating consumer needs before scaling marketing efforts. This gap leaves startups vulnerable to investing in ineffective marketing strategies, ultimately creating a disconnect between their product offerings and actual market demand. Many assume a level of marketing spend that may be unrealistic for early-stage startups, thereby overlooking the critical aspect of budget constraints. Additionally, while data-driven insights are increasingly essential, traditional models often lack built-in mechanisms for AI-driven optimization.

Conclusion

The findings highlight the diverse strengths of each framework while also revealing gaps in areas such as automation and market fit validation. As emerging trends in AI and automation continue to evolve, future frameworks will likely need to integrate product-market fit validation, real-time personalization, and scalability into their core strategies. To close existing gaps, a hybrid framework that integrates AI-driven automation, multi-channel optimization, and sustainable growth strategies would be a useful startup marketing model. Moreover, the absence of an integrated approach to validating consumer needs before scaling marketing efforts leads to inefficiencies, as startups may invest resources in promotional activities that fail to resonate with their intended audience. Addressing this gap necessitates a strategic framework starting from the ideation stage, that explicitly incorporates customer need identification as an integral component of digital marketing.

References

- Andrade, Orberto D. A. 2020. "The Power of Growth Hacking Strategies and the Exponential Growth of UBER." *International Journal of Research in Marketing Management and Sales* 2(1):16–24. doi: 10.33545/26633329.2020.v2.i1a.40.
- Bargoni, Augusto, Fauzia Jabeen, Gabriele Santoro, and Alberto Ferraris. 2023. "Growth Hacking and International Dynamic Marketing Capabilities: A Conceptual Framework and Research Propositions." *International Marketing Review*

41(1):74–106. doi: 10.1108/imr-07-2022-0156.

Burton, Kristin. 2024. “Digital Health Startups: Growth Financing and Valuation Drivers That Signal Strength for Investors.” *Journal of Strategy and Management* 17(4):587–606. doi: 10.1108/jsma-11-2023-0294.

Chaffey, Dave, and P. R. Smith. 2013. *Emarketing Excellence: Planning and Optimizing Your Digital Marketing*. 4th ed. London: Routledge.

Dsouza, Ashlin, and Niyaz Panakaje. 2023. “Performance of Startups Through Digital Marketing.” *International Journal of Case Studies in Business It and Education* 38–50. doi: 10.47992/ijcsbe.2581.6942.0259.

Ghezzi, Antonio, and Angelo Cavallo. 2020. “Agile Business Model Innovation in Digital Entrepreneurship: Lean Startup Approaches.” *Journal of Business Research* 110:519–37. doi: 10.1016/j.jbusres.2018.06.013.

Jin, Fujie, Andy Wu, and Lorin Hitt. 2017. “Social Is the New Financial: How Startup Social Media Activity Influences Funding Outcomes.” P. 13329 in *Academy of management proceedings*. Vol. 1. Academy of Management Briarcliff Manor, NY 10510.

Joel, Olorunyomi S. 2024. “Navigating the Digital Transformation Journey: Strategies for Startup Growth and Innovation in the Digital Era.” *International Journal of Management & Entrepreneurship Research* 6(3):697–706. doi: 10.51594/ijmer.v6i3.881.

Krabokoukis, Thomas. 2025. “Bridging Neuromarketing and Data Analytics in Tourism: An Adaptive Digital Marketing Framework for Hotels and Destinations.” *Tourism and Hospitality* 6(1):12. doi: 10.3390/tourhosp6010012.

Moradi, Sepideh. 2024. “Qualitative Identification of Intervening Factors Affecting Digital Marketing Strategies in Successful Iranian Startups.” *Ijimbob* 4(2):46–53. doi: 10.61838/kman.ijimbob.4.2.6.

Nigam, Nirjhar, Cristiane Benetti, and Sofia A. Johan. 2020. “Digital Start-up Access to Venture Capital Financing: What Signals Quality?” *Emerging Markets Review* 45:100743. doi: 10.1016/j.ememar.2020.100743.

Patel, Neil. 2020. “How to Use AI SEO to Improve Your Website.” Neil Patel. Retrieved July 28, 2023 (<https://neilpatel.com/blog/ai-seo/>).

Patil, Aishwarya, Nagaraj R. Navalgund, and Shashidhar Mahantshetti. 2022. “Digital Marketing Adoption by Start-Ups and SMEs.” *Sdmimd Journal of Management* 13:47. doi: 10.18311/sdmimd/2022/29677.

Rizvanović, Belma, Aneesh Zutshi, António Grilo, and Tahereh Nodehi. 2023. “Linking the Potentials of Extended Digital Marketing Impact and Start-Up Growth: Developing a Macro-Dynamic Framework of Start-Up Growth Drivers Supported by Digital Marketing.” *Technological Forecasting and Social Change* 186:122128. doi: 10.1016/j.techfore.2022.122128.

Weinberg, Gabriel, and Justin Mares. 2015. *Traction: How Any Startup Can Achieve Explosive Customer Growth*. Portfolio.

Zhang, Lin. 2021. “Research on Multi-User Growth Strategy of Pinduoduo Based on AARRR Model.” Pp. 271–76 in. Atlantis Press.

ASSESSING THE ENTREPRENEURIAL ORIENTATION OF THE INFORMATION AND COMMUNICATIONS TECHNOLOGY COMPANIES: A COMPOSITE INDEX

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Keywords: Entrepreneurial orientation, composite index, ICT companies.

Information and communications technology is an ever-growing productive sector. In a globalized, digitalized and constantly evolving world, the field of Information and Communications technology is of particular and remarkable importance. The reason that Information and Communications technology is particularly important in today's era is digital transformation. Schiersch et al. (2023) assert that ICT products are critical to global trade since they are now required as necessary components in the production of all kinds of goods. The commercial landscape has undergone a dramatic transformation thanks to developments in information and communications technology (ICT) that enable companies to access wider markets. Businesses may expand their customer base, increase staffing levels, and increase sales thanks to these advancements. Furthermore, it forces companies to stay abreast of market advancements, introduces them to new ideas and information, and positions them to compete with elite companies (Freund and Weinhold (2002); (2004)).

Entrepreneurial Orientation is a collection of actions associated with proactivity, risk-taking, innovative quality, competitive aggressiveness, and autonomy (Rauch et al. 2009). Three dimensions - risk-taking, proactiveness, and innovativeness - were used in previous research to measure the entrepreneurial orientation construct (Miller, 1983). Later, autonomy and competitive aggressiveness were included as two further characteristics to gauge entrepreneurial orientation (Lumpkin & Dess, 1996). Since more than three decades ago, the concept of entrepreneurial orientation has become one of the most researched in the literature on entrepreneurship and management (Covin et al., 2019). A company's entrepreneurial orientation can be evaluated by examining the distinctively entrepreneurial decision-making styles, processes, and behaviors of its senior management. It describes a company's strategic orientation, which captures the degree of innovation, risk-taking, aggressive competition, and independent and proactive behavior (Andersén, 2010).

For the present research, the period 2019 - 2023 has been chosen, and five European companies. The companies selected are Vaisala, Barco, Hexagon, Bechtle AG, and AVEVA Group. The companies are selected because are multinational companies and are specified in IT technologies. Especially, Vaisala is a Finnish business that manufactures industrial and environmental measurement instruments and services, and meteorological and hydrological services, aviation authorities, defense

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forces, and road authorities are some of their main clientele and markets (Vaisala, 2023). Secondly, Barco is a digital projection and imaging technology firm based in Belgium that targets three main markets: enterprise, healthcare, and entertainment (Barco, 2023). Furthermore, Hexagon (based in Sweden) offers digital reality solutions for applications in the public sector, manufacturing, infrastructure, industrial, and mobility (Hexagon, 2023). Moreover, the business model of international technology corporation Bechtle AG (based in Germany) combines the direct selling of hardware and software goods, information technology services, and the management and upkeep of IT infrastructure for clients in the public and industrial sectors (Bechtle, 2023). Finally, AVEVA Group is a British multinational information technology consulting company headquartered in England. The AVEVA Group provides ship-building and design management, plant and marine catalog information solutions, design, engineering, software, and enterprise solutions (AVEVA, 2023).

To interpret the pillars of the Entrepreneurial Orientation (EO) we used proxies. The same procedure has been applied by Sherif et al. (2019). Especially, for the Innovativeness pillar of the Entrepreneurial Orientation we used Total revenues over the number of employees (Bhaumik and Selarka, 2012). Increased knowledge per employee suggests a stronger capacity for innovation; this effect increases with the gap between (high) revenue and (low) staff numbers, which means The bigger value is the better for estimating the Innovativeness pillar for each company. For the Risk-taking pillar of the Entrepreneurial Orientation, we used the standard deviation (SD) of the return on assets (ROA) (Wright et al., 2007). A strong correlation between high income and high volatility is indicative of benefiting from taking risks. The bigger the value is the better for estimating the Risk Taking pillar for each company. Regarding the Proactiveness pillar of the Entrepreneurial Orientation, we used the percentage of earnings retained by a firm (Kaplan and Zingales, 1997). The profits set aside for future investments are a sign that the company has the chance to be proactive. The bigger the value is the better for estimating the Proactiveness pillar for each company. Moreover, considering the Competitive Aggressiveness pillar of the Entrepreneurial Orientation, we used the gross margin (Krauss, et al. 2005). The lesser the variance between price to customer and cost to firm of supply the further aggressively competitive a firm could be. The smaller the value is the better for estimating the Competitive Aggressiveness pillar for each company. Finally, for the Autonomy pillar of the Entrepreneurial Orientation, we used total revenues over total costs (Schillo, 2011). This suggests investment in employees, as well as owners. The bigger the value is the better for estimating the Autonomy pillar for each company.

The present research has tried to create a composite index that could be able to interpret the performance of the ICT companies based on the Entrepreneurial Orientation pillars. The originality of this research effort is mainly the creation of a composite indicator that can explain the aspects of Entrepreneurial Orientation for the selected companies. Although most research has been based on the creation of a questionnaire (on a seven-point Likert scale) and the validity of assessing firm performance through subjective measures, this research has used a different methodology to be able to demonstrate the effectiveness of Entrepreneurial Orientation in business performance.

Pillars of Entrepreneurial Orientation	Sub-Indicators
Innovativeness	Total revenues over the number of employees
Risk-taking	Standard Deviation (SD) of the Return on Assets (ROA)
Proactiveness	Percentage of Earnings Retained
Competitive Aggressiveness	Gross Margin
Autonomy	Total Revenues over Total Costs

Source: Authors' elaboration.

Table 1: Sub-Indicators of the Composite Index

Our results advance theoretical understanding. The results of this study provide further evidence for claims made by others regarding the beneficial effects of entrepreneurial orientation on company performance among others (e.g., Barringer & Bluedorn, 1999; Zahra & Covin, 1995) that entrepreneurial orientation is essential to business ventures and has a beneficial effect on company performance. Several writers have noted that the procedures for organization, decision-making techniques, and ways of thinking that a company implements to act entrepreneurially are what lead to the presence of EO within the company. A business develops an entrepreneurial orientation when it possesses creativity, proactivity, autonomy, competitive aggressiveness, and risk-taking in combination.

References

- Andersén, J. (2010). A critical examination of the EO-performance relationship. *International Journal of Entrepreneurial Behavior & Research*, 16(4), 309–328.
- Aveva (2023) About Aveva. <https://www.aveva.com/en/about/>
- Barco (2023) About Barco. <https://www.barco.com/en/about/this-is-barco>
- Barringer, B. R., & Bluedorn, A. C. (1999). The relationship between corporate entrepreneurship and strategic management. *Strategic Management Journal*, 20(5), 421–444.
- Bechtle (2023) About Bechtle – Overview. <https://www.bechtle.com/de-en/about-bechtle>
- Bhaumik, S.K. and Selarka, E. (2012) Does ownership concentration improve M&A outcomes in emerging markets?: Evidence from India, *Journal of Corporate Finance*, 18(4), 717–726.
- Covin, J. G., Wales, W., & J. (2019). Crafting high-impact entrepreneurial orientation research: Some suggested guidelines. *Entrepreneurship Theory and Practice*, 43(1), 3–18.
- Freund, C. & Weinhold, D. (2002) The internet and international trade in services. *American Economic Review*, 92(2), 236–240
- Freund, C. L., & Weinhold, D. (2004). The effect of the Internet on international trade. *Journal of International Economics*, 62(1), 171–189.
- Hexagon (2023) Vision, mission, and core values. <https://hexagon.com/company/our-story/vision-mission-values>
- Kaplan, S.N. and Zingales, L. (1997) Do investment-cash flow sensitivities pro-

vide useful measures of financing constraints?, *The Quarterly Journal of Economics*, 112(1), pp.169–215.

Krauss, S.I., Frese, M., Friedrich, C. and Unger, J.M. (2005) Entrepreneurial orientation: a psychological model of success among southern African small business owners', *European Journal of Work and Organizational Psychology*, 14(3), 315–344.

Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review*, 21(1), 135–172.

Miller, D. (1983). The Correlates of Entrepreneurship in Three Types of Firms. *Management Science*, 770-791.

Rauch, A., Wiklund, J., Frese, M., & Lumpkin, G. T. (2009). Entrepreneurial Orientation and Business performance: An Assessment of Past Research and Suggestions for the Future. *Entrepreneurship Theory and Practice*, 761-786.

Schiersch, A. Bertschek, I. & Niebel, T. (2023) Diversify or not? The link between global sourcing of ICT goods and firm performance, DIW Discussion Papers, No. 2043, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin.

Schillo, R. S. (2011). Entrepreneurial orientation and company performance: Can the academic literature guide managers? *Technology Innovation Management Review*, 1(2), 20-25.

Sherif, M. Galloway, L. and Zarrouk, H. (2019) Performance and entrepreneurial orientation in SMEs: the case of Abu Dhabi *International Journal Accounting, Auditing and Performance Evaluation*, 15(3), 241-261.

Vaisala (2023)Vaisala in brief, <https://www.vaisala.com/en>

Wright, P., Kroll, M., Krug, J.A. and Pettus, M. (2007) Influences of top management team incentives on firm risk taking, *Strategic Management Journal*, 28, 81-89.

Zahra, S. A., & Covin, J. G. (1995). Contextual influences on the corporate entrepreneurship–performance relationship: A longitudinal analysis. *Journal of Business Venturing*, 10(1), 43-58.

Session D4

AI & DATA: CHALLENGES AND OPPORTUNITIES FOR MANAGEMENT RESEARCH A Panel Roundtable Discussion

Chair: Harris Kyriakou, ESSEC, France

AI & DATA: CHALLENGES AND OPPORTUNITIES FOR MANAGEMENT RESEARCH A Panel Roundtable Discussion

Moderator:

- **Dr. Harris Kyriakou**, Associate Professor at ESSEC Business School (France), where he focuses on the intersection between collective and artificial intelligence. Prof. Kyriakou is the recipient of the Early Career Award by the Association for Information Systems and has served as an advisor on digitization issues for the European Commission. Prior to joining ESSEC, Prof. Kyriakou was a professor at IESE Business School.

Panel members:

1. **Dr. Cristina Alaimo**, Associate Professor at ESSEC Business School (France), and Visiting Research Fellow and former Assistant Professor at Surrey Business School (University of Surrey).
2. **Dr. Nikos Mylonopoulos**, Professor of Digital Business at ALBA Graduate Business School, The American College of Greece and Director of the SEV Center of Excellence in Creative Leadership.
3. **Dr. Konstantina Valogianni**, Associate Professor at IE Business School, where she works on real-world problems which require algorithmic solutions and tangible, applicable results. Her research is based on the AI industry, which has granted her vast insight into the practitioners' point of view.

Abstract:

Emerging technologies are increasingly responsible for the disruption, creation, and demise of companies and industries. At the heart of this change is datafication and increased digitalization, with interdisciplinary management research and a vibrant community of scholars starting to shed light on the matter. Against this backdrop, we believe the time is ripe to bring together leading scholars with different foci and methodological preferences to discuss, provide direction, as well as debate, how empirical and theoretical work on AI and data can affect management theory and practice.

In an effort to consolidate knowledge, the purpose of this panel is to take stock of what we know regarding the role of data and AI, as well as where opportunities lie to contribute to our cumulative knowledge.

The primary goal of our roundtable is for panelists and participants alike to learn from one another, and to stimulate a conversation that cuts across different paradigms, methodologies, and disciplines. Our focus will be twofold: On the one hand, rather than black boxing AI technologies and the crucial role of data, we will be focusing on their unique characteristics and the opportunities for unique insights for scholars and practitioners alike. On the other hand, we will focus on identifying the challenges that arise due to the increased permeation of data and AI. Consequently, our roundtable will be structured and revolve around the following overarching questions:

1. What's different about currently data and AI?
 2. What are the opportunities for management research on data and AI?
 3. What are the challenges for management research on data and AI?
 4. What are the topics that future data and AI management research should focus on?
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Session A5

HUMAN-AI INTERACTION AND BEHAVIORAL INSIGHTS

Chair: George Baltas, Athens University of Economics and Business,
Greece

TOO MUCH OF A GOOD THING? THE NEGATIVE IMPACT OF HIGH-PERFORMING AI TEAMMATES ON HUMAN PERFORMANCE

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Keywords: Human-AI collaboration, human-AI teams, AI teammates.

Introduction

The rise of GenAI is making human-AI teamwork increasingly common in the workplace (Musick et al., 2021). Unlike virtual assistants, AI teammates act as equal partners in task completion in human-AI teams (Seeber et al., 2020). To this end, AI teammates need to be adaptive to changing collaborative situations, while human team members must have the skills to adjust to the AI teammates' actions (Hauptman et al., 2023). We performed a series of three studies to explore under what circumstance the presence of AI teammates enhances or hinders team (member) performance.

Background and hypotheses

Studies on human-AI hybrids primarily focus on acceptance and attitudes toward AI-assisted decisions across domains (Jussupow et al., 2024; Kawaguchi, 2021; Dietvorst et al., 2018; Fügener et al., 2021; van den Broek et al., 2022; Jussupow et al., 2021). As practitioners' expectations of GenAI's creative potential grow (HBR Editors, 2024), it is important to study GenAI's application in creative collaboration, in particular the effect of AI teammates' performance on human performance in that context.

In our research, we study AI teammate performance as the ability to generate diverse, high-quality, and non-repetitive ideas during brainstorming tasks (Reinig & Briggs, 2008; Dean et al., 2006). Social loafing theory suggests that as perceived individual identifiability decreases in group settings, motivation and effort may decline (Williams et al., 1981; Latané et al., 1979). In human-AI teams with a high-performing AI teammate, human members may experience reduced identifiability, leading to decreased motivation and engagement in the task. This effect may be exacerbated in computer-mediated environments, where social presence is already diminished (Blaskovich, 2008; Chidambaram & Tung, 2005). In the context of a high-performing AI teammate, human members might view their inputs as less essential, potentially leading to reduced cognitive effort in idea generation (De Dreu et al., 2008):

H1: The performance of the AI teammate negatively influences individual member's performance.

Drawing on expectancy-value theory (Karau & Williams, 1993; Vroom, 1964), we argue that human teammates with trustworthy and high-performing AI teammates may perceive their individual efforts as less instrumental, leading to motivational losses (Kerr & Bruun, 1983; Shepperd, 1993). Furthermore, when interacting with a highly trusted, high-performing AI teammate, human members might view their inputs as less essential, potentially leading to reduced cognitive effort in collaborative

tasks (De Dreu et al., 2008; Nijstad et al., 2006). In human-AI teams, this could manifest as reduced individual effort when trust in the AI's capabilities is high:

H2: The negative impact of an AI teammate's performance on individual members' performance is mediated by trust in the AI teammate and social loafing tendency.

In human-AI teams, comparing oneself to a high-performing human teammate may be more self-relevant and thus more motivating than comparing to an AI teammate (Epley et al., 2007; Waytz & Norton, 2014). The motivation to match a high-performing human colleague may counteract the tendency to reduce effort when working with a capable AI teammate (Jung et al., 2010; Karau & Williams, 1993). The presence of a high-performing human teammate may heighten perceptions of task importance and mitigate the negative effects of AI overperformance, which can attenuate social loafing tendencies. Thus, we propose that when a human teammate is perceived as contributing significantly, individuals may feel more compelled to match their efforts, even in the presence of a highly capable AI:

H3: The perceived performance of a human teammate moderates the relationship between AI teammate's performance and individual members' performance, such that the negative effect of high AI teammate's performance on individual performance is attenuated when human teammate's performance is perceived as high.

The impact of AI-augmented work on individual performance may vary across users' expertise levels. Within AI-augmented work, experts may demonstrate algorithmic aversion, placing greater reliance on their own judgment due to higher self-efficacy and perceived expertise (Logg et al., 2019; Dietvorst et al., 2015). Conversely, novices may tend to show greater compliance with AI teammates due to lower self-efficacy in the task domain (Jussupow et al., 2021; Rzepka & Berger, 2018). The complementary nature of AI to novices' limited skills or knowledge may increase their expectancy that using the AI will lead to improved performance (Burton et al., 2020):

H4: The relationship between domain-specific knowledge and individual members' performance is moderated by the AI teammate's performance, such that the positive effect of domain-specific knowledge on individual performance is attenuated when working with a high-performing AI teammate, compared to working with a low-performing AI teammate.

Method

We recruited participants through social media. We employed a brainstorming task where three-member teams (two human and one AI teammate) provided ideas for a fictional retail company's digital transformation. Over three consecutive weeks, participants proposed solutions from marketing, logistics, and organizational structure perspectives. The perceived meaningfulness of the task was assessed after each task description.

Participants used *AI mate*, a custom-built system featuring a chat room, idea generation area, and idea processing area. Teams were trained on *AI mate* usage prior to the sessions. The experiment manipulated the AI teammate's idea quality at two levels (high and low) resulting in a one-factor between-subjects design. Participants completed surveys before and after each session. Individual brainstorming perfor-

mance was evaluated using idea quantity and quality metrics, with quality assessed by blind raters. Self-reported measures collected data on perceived human and AI teammate performance, domain-specific knowledge, trust in the AI teammate, social loafing tendency, task meaningfulness, process satisfaction, and familiarity with teammates.

Results

Study 1 tested the effect of AI teammate performance on team members' performance, manipulating AI performance as a single between-subjects factor using 204 participants from 102 teams. Participants found the task meaningful ($M_{\text{meaning}}=4.00$, $SD_{\text{meaning}}=0.652$) and enjoyable ($M_{\text{satis}}=4.125$, $SD_{\text{satis}}=0.690$). An ANOVA revealed that individuals produced more ideas ($M_{\text{low}}=3.863$, $SD_{\text{low}}=1.945$; $M_{\text{high}}=2.971$, $SD_{\text{high}}=2.113$; $F(1, 200)=10.377$, $p<0.01$), higher overall quality ideas ($M_{\text{low}}=6.269$, $SD_{\text{low}}=3.887$; $M_{\text{high}}=3.917$, $SD_{\text{high}}=3.187$; $F(1, 200)=21.854$, $p<0.001$), and more good ideas ($M_{\text{low}}=0.456$, $SD_{\text{low}}=0.622$; $M_{\text{high}}=0.103$, $SD_{\text{high}}=0.354$; $F(1, 200)=22.118$, $p<0.001$) when collaborating with a low-performing AI teammate compared to a high-performing one, supporting H1.

Study 2 examined the interplay between AI teammate performance, perceived human teammate performance, and domain-specific knowledge on individual performance using 202 participants. Participants found the task meaningful ($M_{\text{meaning}}=4.122$, $SD_{\text{meaning}}=0.608$) and satisfactory ($M_{\text{satis}}=4.223$, $SD_{\text{satis}}=0.598$). Replicating Study 1, AI teammate performance significantly affected the number of ideas ($M_{\text{low}}=3.83$, $SD_{\text{low}}=2.318$; $M_{\text{high}}=2.755$, $SD_{\text{high}}=1.726$; $F(1, 192)=13.808$, $p<0.001$), overall idea quality ($M_{\text{low}}=6.69$, $SD_{\text{low}}=5.445$; $M_{\text{high}}=3.726$, $SD_{\text{high}}=3.157$; $F(1, 192)=21.269$, $p<0.001$), and number of good ideas ($M_{\text{low}}=0.21$, $SD_{\text{low}}=0.537$; $M_{\text{high}}=0.059$, $SD_{\text{high}}=0.275$; $F(1, 192)=7.054$, $p<0.01$). Perceived human teammate performance moderated the effects of AI teammate performance on idea quality (overall quality: $\beta=1.349$, $p<0.1$; number of good ideas: $\beta=0.137$, $p<0.1$) but not on idea quantity ($\beta=0.094$, $p>0.1$), partially supporting H3. AI teammate performance moderated the impact of domain-specific knowledge on idea quantity ($\beta=-0.618$, $p<0.1$) and quality (overall quality: $\beta=-1.716$, $p<0.05$; number of good ideas: $\beta=-0.176$, $p<0.05$), supporting H4. Interestingly, AI teammate performance negatively influenced high-knowledge members' performance but had no significant influence on low-knowledge members' performance.

Study 3 investigated how AI teammate performance influences team members' performance, as proposed in H2 using 196 participants. Participants found the task meaningful ($M_{\text{meaning}}=4.100$, $SD_{\text{meaning}}=0.671$) and satisfactory ($M_{\text{satis}}=4.148$, $SD_{\text{satis}}=0.698$). Replicating Study 1, AI teammate performance significantly affected the number of ideas ($M_{\text{low}}=3.735$, $SD_{\text{low}}=1.938$; $M_{\text{high}}=2.643$, $SD_{\text{high}}=1.725$; $F(1, 192)=17.897$, $p<0.001$), overall idea quality ($M_{\text{low}}=6.393$, $SD_{\text{low}}=4.343$; $M_{\text{high}}=3.398$, $SD_{\text{high}}=2.762$; $F(1, 192)=33.338$, $p<0.001$), and number of good ideas ($M_{\text{low}}=0.270$, $SD_{\text{low}}=0.638$; $M_{\text{high}}=0.071$, $SD_{\text{high}}=0.278$; $F(1, 192)=7.165$, $p<0.01$). AI teammate performance positively affected trust in the AI teammate ($M_{\text{low}}=3.568$, $SD_{\text{low}}=0.987$; $M_{\text{high}}=4.218$, $SD_{\text{high}}=0.684$; $F(1, 192)=28.129$, $p<0.01$) and social loafing tendency ($M_{\text{low}}=2.342$, $SD_{\text{low}}=0.943$; $M_{\text{high}}=2.694$, $SD_{\text{high}}=1.116$; $F(1, 192)=5.792$, $p<0.05$). PROCESS Model 6 re-

vealed that trust in the AI teammate and social loafing tendency mediated the influence of AI teammate performance on individual performance, supporting H2.

Discussion and conclusions

We examined the impact of high-performing AI teammates on human creativity, revealing unexpected consequences. While AI can enhance trust within teams, it also fosters social loafing, leading to reduced individual contributions. However, when human teammates are perceived as high performing, this effect is mitigated through upward social comparison. Additionally, AI equalizes productivity disparities, not by uplifting low-knowledge members but by decreasing the performance of high-knowledge members. These findings challenge the assumption that AI consistently enhances creativity.

Our work extends human-AI teaming research to creative problem-solving and highlights the role of AI as a collaborator rather than an assistant. Practically, managers should carefully integrate high-performing AI teammates, as they may inadvertently hinder human engagement. Future research should explore strategies to counteract social loafing and refine human-AI collaboration, ensuring AI enhances, rather than diminishes, human contributions.

References

- Alnuaimi, O. A., Robert, L. P., & Maruping, L. M. (2010). Team size, dispersion, and social loafing in technology-supported teams: A perspective on the theory of moral disengagement. *Journal of Management Information Systems*, 27(1), 203–230.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. Macmillan.
- Blaskovich, J. L. (2008). Exploring the effect of distance: An experimental investigation of virtual collaboration, social loafing, and group decisions. *Journal of Information Systems*, 22(1), 27–46.
- Boussiou, L., Lane, N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem solving. Retrieved from <https://papers.ssrn.com/abstract=4533642>.
- Burton, J. W., Stein, M., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision-making. *Journal of Behavioral Decision Making*, 33(2), 220–239.
- Chidambaram, L., & Tung, L. L. (2005). Is out of sight, out of mind? An empirical study of social loafing in technology-supported groups. *Information Systems Research*, 16(2), 149–168.
- David, D. C., Nicola, M. B., & Ben, F. (2023). How generative AI could disrupt creative work: Three scenarios—and how to navigate them. *Harvard Business Review Digital Articles*, 1–9.
- De Dreu, C. K. W., Nijstad, B. A., & van Knippenberg, D. (2008). Motivated information processing in group judgment and decision making. *Personality and Social Psychology Review*, 12(1), 22–49.
- Dean, D., Hender, J., Rodgers, T., & Santanen, E. (2006). Identifying quality, novel, and creative ideas: Constructs and scales for idea evaluation. *Journal of the Association for Information Systems*, 7(10), 646–699.
- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion:

People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114–126.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, 64(3), 1155–1170.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864–886.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021). Will humans-in-the-loop become borgs? Merits and pitfalls of working with AI. *MIS Quarterly*, 45(3), 1527–1556.

Hauptman, A. I., Schelble, B. G., McNeese, N. J., & Madathil, K. C. (2023). Adapt and overcome: Perceptions of adaptive autonomous agents for human-AI teaming. *Computers in Human Behavior*, 138, 107451.

HBR Editors. (2024). Don't let Gen AI limit your team's creativity. *Harvard Business Review*, 102(2), 17–21.

Jussupow, E., Benbasat, I., & Heinzl, A. (2024). An integrative perspective on algorithm aversion and appreciation in decision-making. *MIS Quarterly*, 48(4), 1575–1590.

Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research*, 32(3), 713–735.

Karau, S. J., & Williams, K. D. (1993). Social loafing: A meta-analytic review and theoretical integration. *Journal of Personality and Social Psychology*, 65(4), 681–706.

Kawaguchi, K. (2021). When will workers follow an algorithm? A field experiment with a retail business. *Management Science*, 67(3), 1670–1695.

Kerr, N. L., & Bruun, S. E. (1983). Dispensability of member effort and group motivation losses: Free-rider effects. *Journal of Personality and Social Psychology*, 44(1), 78–94.

Latané, B., Williams, K., & Harkins, S. (1979). Many hands make light the work: The causes and consequences of social loafing. *Journal of Personality and Social Psychology*, 37(6), 822–832.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90–103.

Musick, G., O'Neill, T. A., Schelble, B. G., McNeese, N. J., & Henke, J. B. (2021). What happens when humans believe their teammate is an AI? An investigation into humans teaming with autonomy. *Computers in Human Behavior*, 122, 106852.

Nijstad, B. A., Stroebe, W., & Lodewijkx, H. F. M. (2006). The illusion of group productivity: A reduction of failures explanation. *European Journal of Social Psychology*, 36(1), 31–48.

Reinig, B. A., & Briggs, R. O. (2008). On the relationship between idea-quantity and idea-quality during ideation. *Group Decision and Negotiation*, 17(5), 403–420.

Rzepka, C., & Berger, B. (2018). Deep learning for knowledge-intensive work automation: Challenges and opportunities in the insurance industry. *Electronic*

Markets, 28(4), 537–553.

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., & Maier, R. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, 57(2), 103174.

Shepperd, J. A. (1993). Productivity loss in performance groups: A motivation analysis. *Psychological Bulletin*, 113(1), 67–81.

Vroom, V. H. (1964). *Work and motivation*. Wiley.

Waytz, A., & Norton, M. I. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking—not feeling—jobs. *Emotion*, 14(2), 434–444.

Williams, K. D., Harkins, S. G., & Latané, B. (1981). Identifiability as a deterrent to social loafing: Two cheering experiments. *Journal of Personality and Social Psychology*, 40(2), 303–311.

CAN PEOPLE IDENTIFY WHO IS RESPONDING? FACTORS AFFECTING PERCEPTIONS OF AI VS HUMAN AGENTS

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Keywords: Anthropomorphism, AI chatbots, AI emotional intelligence.

In recent years, artificial intelligence has advanced dramatically and started establishing itself in a number of industries, changing how they operate. The development of AI technology and the widespread adoption of chatbots has changed the way businesses interact with customers. These systems are now a normal part of everyday activities, especially within customer support. AI does not directly replace jobs but takes on specific tasks within them, starting from simple mechanical processes and gradually moving on to more complex ones that require the combination of different forms of intelligence (Huang and Rust, 2018). Chatbots are proving to be powerful tools in customer service, with the ability to respond effectively to demands, without being easily distinguishable from human responses. The inability to identify meaningful differences is due to the anthropomorphic dimension of chatbots that is substantially enhanced by the integration of emotional intelligence (Luo et al. 2023). However, despite the integration and apparent effectiveness of these technologies, questions arise about how users perceive responses coming from artificial intelligence compared to the responses of a human representative. Although AI can mimic certain human functions, fully understanding emotions remains a challenge and needs to be researched.

This study investigates the anthropomorphic dimension of artificial intelligence (AI) and users' ability to recognize the author of responses in customer service environments, specifically in the hospitality industry. Through popular evaluation platforms, it examines users' ability to identify which responses are from chatbots and which are from human agents by essentially comparing AI responses to actual responses from human agents as formulated on that platform. Through qualitative methodology, namely interviews, the research attempts to determine how AI characteristics influence users' emotional reactions and satisfaction when interacting with chatbots, versus those of human agents. The research is based on a theoretical background that includes the concept of anthropomorphism, which is the attribution of human characteristics and behaviours to inanimate objects or non-human entities (Airenti 2015; Epley et al., 2007). In the context of AI, anthropomorphism is manifested through various factors involving the use of linguistic and visual elements that mimic human communication, as well as through characteristics such as empathy and emotional intelligence. These characteristics can influence the perception regarding the trust, warmth and effectiveness of responses provided by both chatbots and other agents (Cheng et al, 2022; Schanke et al, 2021). The research highlights the importance of emotional intelligence in AI, focusing on the role of empathy and emotional language. Artificial empathy is defined as the ability of a digital agent to recognise and respond appropriately to users' emotions, which can enhance users'

trust and emotional engagement (Liu-Thompkins et al., 2022).

For the empirical study, interviews were conducted with ten participants, half of whom had previous experience with the use of chatbots, while the rest had no previous contact with such applications. Participants were asked to evaluate four scenarios of negative reviews, in which the responses from the human representatives as formulated in the evaluation platform as well as those generated by the chatbot were presented. An important aspect of the methodology was that participants did not know the origin of the responses beforehand, which allowed for the collection of authentic responses without bias. During the course of the study, several factors identified in the literature that directly affect the perception of anthropomorphism were examined. The research identified six key categories influencing users' perceptions and satisfaction with responses. The first category is "Aggression, Indifference, and Irony", highlighting the negative impact of aggressive, indifferent, or ironic tones in responses. The second category is "Empathy/Lack of Empathy", emphasizing the role of empathy in enhancing or undermining emotional engagement. The third category is "Negative Experience Acknowledgement/Ignorance", showing the importance of recognizing negative experiences to prevent feelings of dismissal. The fourth category is "Problem-Solving Approach", underlining the significance of addressing customer concerns through solutions rather than focusing solely on positive aspects. The fifth category is "Language Reflecting Empathy", illustrating how empathetic phrasing improves satisfaction by acknowledging customer concerns. The last category is "Exchange Theory", involving promises of future rewards, such as better service or discounts.

Participants showed a preference for responses that included direct acknowledgement and addressing of negative comments, while responses that ignored or downplayed the negative aspects of their experience were judged negatively. The research concluded that users tended to prefer responses that showed empathy and understanding, often through the use of emotive language, about the customer's negative experience and directly addressed the problems highlighted in the comments. In particular, chatbots' responses were those that appeared to demonstrate these characteristics and were preferred over human responses, which often focus only on the positive aspects of the experience presented in the customer's review without acknowledging or addressing the negative comments. The findings suggest that AI anthropomorphism can improve the user experience and address user experience equally or, in some cases, more effectively than human agents if used appropriately.

Furthermore, this research examines the possibility of identifying the origin of the answers. Without the participants knowing the origin of the answers, i.e., whether they were written by a chatbot or a human agent, the possibility of identifying the author and the satisfaction they received from each answer was examined. The results of the survey indicate that users find it difficult to distinguish differences regarding the origin of the answers; more specifically, in none of the scenarios presented did the author seem to be evident. However, elements that betrayed the human agent in some cases were the negative emotional nuance of the human agent

in the comment, as well as the repetition of elements of the negative review. Through the analysis of the interviews, an additional interesting finding emerged regarding the participants' expectations regarding the emotional impact and the origin of the responses. Participants, without initially knowing the origin of the responses, judged the responses that had been produced by the chatbot, which subsequently, i.e., when revealing the origin, caused strong feelings of surprise. Several participants, after being informed that the responses they considered more satisfactory and felt that they were better managing the emotions came from a chatbot, were surprised and expressed doubts about the management of the answers by the hotel representatives.

From a theoretical point of view, this research contributes to the literature on the anthropomorphism and emotional intelligence in artificial intelligence. In particular, it highlights the role of emotional responses in shaping user satisfaction. The six categories identified offer a new perspective on the management of negative feedback in the hospitality industry and the service sector in general. On a practical level, the findings suggest the need to improve the design of chatbots, with a focus on their emotion in order to achieve a more human-centric approach. Incorporating linguistic and emotional features into responses can improve users' overall perception of service quality. At this time and based on the findings of this qualitative research, quantitative research will be conducted to examine the dimensions of AI anthropomorphism in a larger sample and scope. Overall, this paper offers a multi-dimensional approach to understanding the emotional impact of AI. The findings highlight the importance of emotional intelligence and the adaptability of chatbots to it as a critical parameter for building future AI systems.

References

- Airenti, G. (2015) 'The cognitive bases of anthropomorphism: from relatedness to empathy,' *International Journal of Social Robotics*, 7(1), pp. 117-127. <https://doi.org/10.1007/s12369-014-0263-x>.
- Cheng, X. et al. (2022) 'Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms,' *Information Processing & Management*, 59(3), p. 102940. <https://doi.org/10.1016/j.ipm.2022.102940>.
- Epley, N., Waytz, A. and Cacioppo, J.T. (2007) 'On seeing human: A three-factor theory of anthropomorphism.,' *Psychological Review*, 114(4), pp. 864-886. <https://doi.org/10.1037/0033-295x.114.4.864>.
- Huang, M.-H. and Rust, R.T. (2018) 'Artificial intelligence in service,' *Journal of Service Research*, 21(2), pp. 155-172. <https://doi.org/10.1177/1094670517752459>.
- Liu-Thompkins, Y., Okazaki, S. and Li, H. (2022) 'Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience,' *Journal of the Academy of Marketing Science*, 50(6), pp. 1198-1218. <https://doi.org/10.1007/s11747-022-00892-5>.
- Luo, B., Lau, R.Y.K. and Li, C. (2023) 'Emotion-regulatory chatbots for enhancing consumer servicing: An interpersonal emotion management approach,' *Information & Management*, 60(5), p. 103794. <https://doi.org/10.1016/j.im.2023.103794>.
- Schanke, S., Burtch, G. and Ray, G. (2021) 'Estimating the impact of "Humaniz-

ing” customer service chatbots,’ *Information Systems Research*, 32(3), pp. 736-751.
<https://doi.org/10.1287/isre.2021.1015>.

ADOPTING AI IN EVERYDAY LIFE: UNDERSTANDING USER INTENTIONS AND BEHAVIORS THROUGH AN ENHANCED THEORETICAL MODEL

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Keywords: Artificial intelligence, UTAUT2, technology adoption, PLS-SEM.

Artificial Intelligence (AI) has become a pivotal force in reshaping industries and consumer experiences by enhancing personalization, efficiency, and decision-making processes (Kumar et al., 2024). Smart technologies have been integrated into daily life, which can help increase productivity, enhance the use of resources and make decisions based on the information (Kristoffersen et al., 2020). While there is widespread recognition of its potential to transform, the adoption of AI-enabled products and services by consumers is influenced by a range of behavioral, technological and socio-economic factors. This study investigates the key elements that shape the adoption of AI technology, building upon the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model and incorporating additional constructs relevant to consumer use.

The research objectives, therefore, are to examine the factors that influence AI uptake and analyze the barriers and enablers to the utilization of AI solutions. The analysis focuses on variables that capture both intrinsic motivators, such as personal interest and perceived benefits, and external influences, such as economic capacity and technological usability (Davis, 1989). Moreover, the research involves factors like health benefits, convenience, data security, personal innovativeness, hedonic motivation, effort expectancy and habit. These variables were chosen with the aim of having a broad picture of AI goods and services acceptance across diverse populations and for various uses, from smart assistants, home automation and control systems, voice recognition, health monitoring devices and applications.

The UTAUT2 model extends traditional technology acceptance theories by incorporating constructs such as hedonic motivation, price value, and habit (Venkatesh et al., 2012). In adapting this framework to the context of AI adoption, the study examined how AI products increase well-being, reduce routine activities, protect data privacy and target users predisposed to adopt new technologies. The use of annual income and age as control factors in the model shows that financial aspects can play a role in taking up advanced technologies, especially in markets with high-cost AI products, whereas younger people tend to have an increased use of such solutions. The research focuses on these constructs in order to determine the conditions under which consumers are more likely to accept and consistently use AI solutions.

The study employed a quantitative approach and used a structured questionnaire as an instrument for data collection. The questionnaire was distributed in Greek, through social media platforms and email communication between November and December 2024. The research intended to collect demographic profiles, perceptions of AI and behavioral patterns when using AI. Respondents were asked to rate their agreement with statements concerning their experiences and attitudes toward AI

solutions on a five-point Likert scale from strongly disagree to strongly agree. The questionnaire was completed by 235 Greek citizens, intentionally diverse in age, profession and income to ensure a representative dataset.

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data collected because it is an effective statistical method for studying complex models and estimating relationships between multiple constructs at the same time (Hair et al., 2019). The measurement model was tested for internal consistency, convergent validity and discriminant validity using factor loadings, Cronbach's alpha, composite reliability, average variance extracted and HTMT scores. These assessments confirmed that the model's constructs were reliable and valid, thus supporting the results.

Insights into the adoption of AI solutions were revealed in the study. Performance expectance benefits produced by the use of health-related and convenience comfort AI solutions that have a positive impact on users' physical or mental health and/or provide convenience and reduce the effort required from manual tasks turned out to be strong positive predictors of behavioral intention. In a similar vein, the perception of security mattered a lot; products that offered assurances of data privacy and protection against unauthorized access were rated positively (Bansal et al., 2022). In an age of data breaches and privacy concerns, the focus on security features can greatly increase consumer trust and adoption (Muhammad et al., 2018).

Personal innovativeness was found to be another important factor in AI adoption. Those having a tendency to explore and adopt new technologies were more likely to accept AI products; the early adopters and technology enthusiasts are important to the diffusion of AI innovations (Rogers et al., 2014). Moreover, the results indicate that higher-income individuals were more likely to invest in AI technologies, suggesting that financial barriers may restrict accessibility to these technologies to a broader segment of the population (Gefen et al., 2003). Another influential construct was found to be habit, as users who frequently interacted with AI products and services had a higher likelihood of continuing to use them (Sidlauskiene, 2022).

High explanatory power was shown by the final structural model, with significant path coefficients supporting the hypothesized relationships between constructs (Hair Jr et al., 2021). Values for the variance inflation factor (VIF) for all predictors were below the threshold of five, which meant that multicollinearity was not a problem (Kock, 2015). The theoretical model was validated, and evidence was found that the identified factors collectively contribute to the acceptance and sustained use of AI solutions.

The findings suggest that AI products and services must be designed and developed in a way that addresses user concerns regarding usability, security and privacy issues. Personal innovativeness is positively correlated with AI adoption and marketing strategies should focus on early adopters and feature cutting-edge technology that differentiates AI products from traditional technologies. On the other hand, affordability still plays a big role, as income-based disparities can stop people from accessing advanced AI solutions (Ali et al., 2019). Digital inclusivity should be implemented through initiatives that will increase the availability of affordable AI products and services to stakeholders, including policymakers and industry. Moreover, educational campaigns to raise user awareness of the practical benefits of AI

can work to demystify the technology and encourage greater user confidence.

AI adoption differs from standard technology acceptance models because users weigh trust in data security along with their perceived health advantages associated with AI implementations. The study establishes that personal innovativeness creates a greater impact on AI adoption than previous technology adoption because early adopters and technology enthusiasts drive both diffusion and future adoption patterns.

Our study's findings offer practical implications for organizations. A first recommendation is to focus on creating strong data protection systems that provide clear privacy guarantees during AI operations, especially for cases handling sensitive individual information. Moreover, organizations should simultaneously showcase AI products that enhance health because user well-being functions can boost customers' perceptions of these technologies' value. The targeting of early adopters and technologically innovative users brings quick market penetration since they demonstrate strong AI solution usage intent. Organizations need to evaluate AI technology costs while developing financial strategies to decrease price barriers for potential users through different service levels or public stakeholder partnerships. The adoption of AI requires educational programs that explain both practical advantages and safe usage of AI to build trust among users while promoting confidence leading to widespread adoption.

This study makes a valuable contribution to the existing literature by providing a comprehensive analysis of the factors influencing AI adoption and extending the UTAUT2 framework to include context-specific constructs. The findings highlight the multifaceted nature of user acceptance, demonstrating that both individual characteristics and external factors shape behavioral intentions and usage patterns. However, it is important to acknowledge the limitations of the study. The cross-sectional design restricts the ability to draw causal inferences, and the reliance on self-reported data may introduce biases related to social desirability and subjective interpretations.

These limitations present opportunities for future inquiry using a longitudinal design to observe changes in user perceptions over time and including qualitative methods, like in-depth interviews and focus groups, to understand user motivations and frustrations in more depth. Furthermore, comparisons across contexts of diverse cultures and economic backgrounds may bring to light how regional differentiation matters to AI adoption. Future research filling these gaps will provide a more nuanced picture of how technological innovation and the behavior of users interact with societal trends.

Finally, this work highlights the significance of a user-centric design of AI products and services. Understanding the key drivers for AI adoption and identifying potential barriers can enable developers and policymakers to build an inclusive technological ecosystem that not only fosters wide adoption but also strengthens our digital experiences. Health-oriented features, secure data measures and user-friendly interfaces, along with attempts to make the services more affordable and accessible will go a long way to not only impact the trajectory of AI adoption but also to make the digital future more fair.

References

- Ali, M. A., Alam, K., Taylor, B. and Rafiq, S. (2019), "Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data", *Economic Analysis and Policy* 64, 317-328.
- Bansal, G., Rajgopal, K., Chamola, V., Xiong, Z. and Niyato, D. (2022), "Healthcare in metaverse: A survey on current metaverse applications in healthcare", *Ieee Access* 10, 119914-119946.
- Davis, F. D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS quarterly*, 319-340.
- Gefen, D., Karahanna, E. and Straub, D. W. (2003), "Trust and tam in online shopping: An integrated model", *MIS Quarterly* 27 (1), 51-90.
- Hair, J. F., Risher, J. J., Sarstedt, M. and Ringle, C. M. (2019), "When to use and how to report the results of PLS-SEM", *European business review* 31 (1), 2-24.
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M. and Sarstedt, M. (2021), *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage publications.
- Kock, N. (2015), "Common method bias in PLS-SEM: A full collinearity assessment approach", *International Journal of e-Collaboration (ijec)* 11 (4), 1-10.
- Kristoffersen, E., Blomsma, F., Mikalef, P. and Li, J. (2020), "The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies", *Journal of business research* 120, 241-261.
- Kumar, V., Ashraf, A. R. and Nadeem, W. (2024), "AI-powered marketing: What, where, and how?", *International Journal of Information Management* 77, 102783.
- Muhammad, S. S., Dey, B. L. and Weerakkody, V. (2018), "Analysis of factors that influence customers' willingness to leave big data digital footprints on social media: A systematic review of literature", *Information Systems Frontiers* 20, 559-576.
- Rogers, E. M., Singhal, A. and Quinlan, M. M. (2014), "Diffusion of innovations", *An integrated approach to communication theory and research*, Routledge, pp. 432-448.
- Sidlauskiene, J. (2022), "What drives consumers' decisions to use intelligent agent technologies? A systematic review", *Journal of internet commerce* 21 (4), 438-475.
- Venkatesh, V., Thong, J. Y. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS quarterly*, 157-178.
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TRUST AND TRANSPARENCY AROUND AI'S INVESTMENT DECISION-MAKING PROCESSES

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Keywords: Transparency, trust, AI, investment, strategic, decision.

The development and use of artificial intelligence (AI) in the financial markets carry an investment decision-making process paradigm that has greatly uplifted the level of insight, efficiency, and predictive improvement. This reliance on AI has raised serious questions pertaining to the levels of trust and transparency in economy and economic perspectives. This abstract tries to deep into the fundamental issues and opportunities offered by AI-powered investment decisions with a preeminent focus on trust and transparency of the economic units. It assesses the level of explainability, compliance with regulations, along with ethical and technological considerations influencing the trust that stakeholders place in AI-powered investment decision-making processes.

AI has introduced a new dimension to strategic investments by providing data-assisted decision insights, simplifying complex decision-making processes. However, the opacity of AI algorithms, often operating as a “black box,” poses a significant challenge. Establishing trust and ensuring transparency is vital for the application of AI in investment strategies. This article tries to examine the obstacles, solutions, and importance of regulation in fostering trust and transparency in AI systems. AI's application in investments also require cross-disciplinary collaboration among finance, technology, and regulatory experts to develop innovative systems while ensuring accountability. Proper risk assessments and scenario modelling are crucial for stakeholders to mitigate unforeseen outcomes in AI systems. Trust is core to investment decisions as it influences faith in investors and the market. . However, AI in decision-making on investments face obstacles in trust and transparency, biases due to reliance on historical data, regulatory uncertainty regarding AI in finance, cybersecurity vulnerabilities, privacy issues requiring balance between protection and awareness, model decay that challenges relevance in retraining, stakeholder reluctance in adopting AI systems, and interoperability challenges in integrating AI into existing financial infrastructures. Future trends in AI for investments include advancing explainability techniques to balance transparency and accuracy, utilizing blockchain for transparent decision-making and data activity, enabling AI-based Environmental, Social, and Governance (ESG) investments with clear metrics, and fostering collaboration between regulators and industry players to create standard frameworks ensuring transparency and trust. In conclusion, by promoting explainable AI, robust governance frameworks, and ethical practices, the financial industry can maximize the benefits of AI in investment strategies sustainably and effectively. The investigation into AI in financial markets requires a methodology in research for trust and transparency in investment decision-making. There are several types of research methodologies, each having its relative strengths and weaknesses, which would help or hinder the depth and reliability of results found within this domain.

Quantitative research

The essential quantitative research methods are based on numerical data and statistical analysis to identify patterns, correlations, and cause-and-effect relationships. Indeed, one of the widely used approaches in AI and finance is quantitatively allowing large datasets to be analyzed and to provide objective results. Key performance indicators would enable researchers to measure trust and transparency, such as through algorithmic explainability scores, market reaction analyses, metrics with regard to regulatory compliance, and so on.

Advantages:

- Has measurable and objective insights.
- It allows analytics and reproduction of results on large data.
- It enables predictive modeling and testing scenarios for AI decision-making.

Disadvantages:

- It tends to oversimplify complex financial and ethical issues.
- Relies highly on historical data that may bring about biases.
- Lacks capturing qualitative aspects of trust and transparency.

Qualitative research

Qualitative research seeks to explain human perceptions, behaviors, and motivations through interviews, case studies, and thematic analyses. Qualitative studies in the context of AI-powered investments point to stakeholders' trust levels, regulatory concerns, and ethical considerations.

Advantages:

- Gives profound insights into the attitudes and concerns of stakeholders.
- Captures those areas where quantitative models might miss the complexities.
- Flexibility and an exploratory approach are possible on emerging issues pertaining to AI.

Disadvantages:

- Findings are normally subjective and too difficult to generalize.
- Requires significant time and expertise for data collection and analysis.
- Limited ability to quantify impacts on financial performance.

Mixed-methods research

A mixed-methods approach integrates both quantitative and qualitative methodologies to provide a more comprehensive understanding of AI's role in financial decision-making. By combining statistical analysis with stakeholder interviews, researchers can assess both the numerical impact of AI and the human factors affecting trust and transparency.

Advantages:

- Balances statistical rigor with in-depth qualitative insights.
- It gives a wide-ranging view of the strengths and weaknesses AI has in finance.
- The validity of findings can be enhanced by cross-validation through data sources.

Disadvantages:

- It requires huge resources and expertise in both methodologies.
 - Tends to be time-consuming and complex to apply appropriately.
 - Combining different data types may create analytical challenges.
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Session B5

**ANALYTICS, TECHNOLOGY
AND AI IN MARKETING**

Chair: Sourindra Banerjee & Stavroula Spyropoulou, University of
Leeds, UK

THE EFFECT OF SOCIAL IDENTITY ORIENTATION ON RECEPTIVITY TO AI

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Keywords: Artificial intelligence, consumer psychology, social identity, culture.

Abstract

While operational efficiencies and societal benefits have driven research on AI acceptance, much of the focus has been on situational factors, such as AI attributes or task types. However, less is known about the role of individual consumer differences in shaping AI receptivity. This research examines the role of social identity orientation in shaping consumer receptivity toward artificial intelligence (AI). While existing studies on AI acceptance largely focus on situational factors, such as agent or task characteristics, we introduce consumer identity as a critical determinant. Conceptualizing AI as a social actor, we hypothesize that individuals with high social identity orientation, particularly from collectivistic cultures, demonstrate greater AI receptivity through higher identification with AI. This is driven by AI being perceived as an agreeable social agent and agreeableness being a key element to construct a collective identity. Across four studies, including country-level analyses and individual-level experiments, we find consistent evidence supporting these hypotheses. These findings advance understanding in the technology and identity literature. Implications emphasize the need for identity-sensitive AI designs to foster broader consumer acceptance.

SELF-TRACKING TECHNOLOGIES IN SOCIAL CONTEXTS: COMMUNITY MEMBERSHIP IMPLICATIONS FOR USER WELLBEING

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Keywords: Self-tracking technologies, physical inactivity, service design strategy.

Abstract

Physical inactivity is a global problem. A frequent strategy to increase how much one exercises and stay motivated is using self-tracking technologies (STTs). STTs are smart devices and service applications that seek to support consumers' self-improvement efforts, enabling them to collect and monitor their personal performance data (e.g., Fitbit, Strava). Many STTs offer social features, allowing users to join virtual communities. STT service providers commonly encourage users to join and participate in such communities, as membership should keep them returning to the STT. However, whether STT community membership is really beneficial to increase STT users' wellbeing and improve their effort in exercise remains unknown. Using a 6-month longitudinal field study and objective behavioral data, this study shows that STT community membership (vs. individual use) delays user dropout from the service. This effect is explained because STT community membership increases users' eudaimonic happiness. In addition, results show that there is also a downside to STT community membership, as membership (vs. individual use) leads to lower individual effort. In turn, effort increases eudaimonic happiness. This tension is resolved by user self-esteem, which weakens the negative effect of STT community membership on effort. Theoretical and managerial implications for service design strategy are derived from the study's findings.

MANAGING SUPPLY CHAIN DISRUPTIONS IN THE AGE OF TECHNOLOGICAL TURBULENCE

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Keywords: Supply chain disruption, accommodation strategy, supply chain resilience, innovation performance, technological turbulence.

Abstract

Supply chain disruptions pose significant challenges to firms and their performance, requiring them to adopt effective strategies to maintain competitiveness. This is particularly true in dynamic and technology-driven environments. Using dynamic capability theory as the study's theoretical framework, this study focuses on the role of accommodation strategies—where firms adapt their operations to disruptions resulting from competitive acts by supply chain partners—and their impact on performance outcomes, specifically focusing on innovation-related outcomes. Additionally, this study puts a focus on how supply chain resilience and supply chain disruption orientation moderate the relationship between disruption impact and accommodation strategy adoption. Given the increasing role of technology in supply chain operations, the study introduces technological turbulence as a contextual factor, enabling or weakening the effect of disruption impact on innovation performance. Three key research questions guide the study: (1) What is the impact of supply chain disruption and accommodation strategies on innovation performance? (2) How does supply chain resilience moderate this relationship? (3) How does supply chain disruption orientation influence the effectiveness of accommodation strategies? Further the study looks at the role of technological turbulence as a moderator focusing on whether accommodation is more important for innovation performance in technologically turbulent environments.

ECONOMIC INEQUALITY AND PRICE PREMIUMS IN RETAIL MARKETS

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Keywords: Retail analytics, organic food, price premium, economic inequality.

Abstract

Economic inequality is not only a topic in economics, but also has far-reaching implications for other social sciences, including marketing. While it has been suggested that, for a variety of reasons, poorer people tend to pay higher prices for groceries, a phenomenon known as the ‘poverty penalty’, there is otherwise insufficient systematic evidence on whether retail prices vary systematically across regions as a result of changes in regional income distribution. Therefore, this study seeks to answer the following questions: (1) To what extent does economic inequality drive premium pricing strategies in the context of organic foods? (2) How do these strategies differ between national and private label brands? And (3) how do they vary between economically advantaged and disadvantaged regions? We answer these questions by testing four hypotheses. First, we test if economic inequality is positively associated with organic product prices. Second, we test if economic inequality is positively associated with the price premium of organic food relative to conventional food. Next, we tested if national brands moderate the relationship between economic inequality and price premiums more strongly than private labels. Finally, we tested if moderating role in the relationship between economic inequality and price premium is stronger in economically advantaged regions than in economically disadvantaged regions. The empirical context of this study is the U.S. retail market for organic products and uses advanced econometrics models and analytics. This study utilizes Nielsen consumer panel data and data from the U.S. Census Bureau. In this study, we make three contributions. First, it enriches the literature on the impact of economic factors, particularly economic inequality, on the retail product pricing, especially in contexts characterized by premium products (e.g. organic food). Second, while some studies have found that the larger gap between high income and low income group leads to higher retail prices, our research could reveal whether these trends hold true in the organic market or whether the premium nature of organic products introduces different pricing patterns based on income inequality. Moreover, the study attempts to investigate the premium pricing of organic products might not only reflect production costs but also the broader socio-economic context, including income inequality and market segmentation.

Session C5

AI IN ENTREPRENEURSHIP AND ENTREPRENEURIAL FINANCE: RESEARCH CHALLENGES AND PRACTICAL IMPLICATIONS FOR BUSINESS SCHOOLS A Panel Roundtable Discussion

**Chair: Vincenzo Capizzi, UPO - Università del Piemonte Orientale,
Italy**

AI IN ENTREPRENEURSHIP AND ENTREPRENEURIAL FINANCE: RESEARCH CHALLENGES AND PRACTICAL IMPLICATIONS FOR BUSINESS SCHOOLS

A Panel Roundtable Discussion

Moderator:

- **Dr. Vincenzo Capizzi**, Full Professor at the Department of Economics and Business Studies of the Università del Piemonte Orientale, and Vice Rector of the same university.

Panel members:

1. **Mr. Carlo Allevi**, CEO of WeAreStarting (Crowdfunding Platform).
2. **Dr. Stefano Bonini**, Tenured Associate Professor of Finance and Director of International Relations at Stevens Institute of Technology (USA).
3. **Dr. Vincenzo Buttice**, Associate Professor at the School of Management of Politecnico di Milano, and Lecturer in Entrepreneurial Finance and Sustainable Finance at the Polimi Graduate School of Management (Italy).
4. **Dr. Matthias Mattusch**, Professor and Chair of Finance and Financial Technologies at the Technical University of Dresden (Germany).
5. **Dr. Sasan Mansouri**, Assistant Professor at the University of Groningen (Netherlands), where his expertise lies in the realms of Digitalization and Artificial Intelligence, particularly as they apply to finance and accounting.

Abstract:

The integration of Artificial Intelligence (AI) into entrepreneurship and finance marks a transformative epoch in the business landscape. This special session aims to delve into the profound impacts and evolving role of AI in these dynamic fields. AI's capabilities, ranging from predictive analytics to sophisticated decision-making algorithms, have redefined traditional business models and financial strategies, presenting both unparalleled opportunities and new challenges.

In entrepreneurship, AI has become a pivotal tool for identifying market gaps, optimizing operations, and enhancing customer experiences. Startups and established businesses alike are leveraging AI to gain competitive advantages and drive innovation. Meanwhile, in finance, AI is revolutionizing areas like risk assessment, fraud detection, portfolio management, and algorithmic trading, reshaping the industry's operational dynamics. However, alongside these advancements, AI raises critical questions concerning ethics, data security, employment, and the wider societal impacts of automated decision-making. This special session will explore how entrepreneurs and financial institutions are navigating these challenges, adapting to AI's potential, and shaping the future of business and finance as well as of executive education delivered by Business Schools.

Session D5

AI-POWERED SUSTAINABILITY: FROM POLICY INSIGHTS TO EDUCATIONAL INNOVATION

Chair: Eric Soderquist, Athens University of Economics and Business,
Greece

DATA-DRIVEN INSIGHTS ON HUMAN SECURITY INTEGRATION IN EU GREEN DEAL POLICIES

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Keywords: Human security, machine learning, EU green deal, sustainability, climate policy.

Introduction

Human Security (HS) has evolved into a multidisciplinary concept that reframes the notion of security to focus on protecting and empowering individuals, rather than merely safeguarding national borders. Originally posited by the United Nations Development Programme (UNDP, 1994) and further elaborated by the Commission on Human Security (2003), HS encompasses dimensions such as economic stability, food and health availability, environmental sustainability, communal cohesion, political freedom, and personal safety. In recent years technological security has entered the debate, reflecting the need to protect people against threats arising from digitalization and cyber vulnerabilities.

The European Green Deal (EGD) aims to achieve sustainability through a transformative approach that balances environmental, economic, and social dimensions. Multi-faceted initiatives such as the EGD often emphasize mitigating climate change and fostering economic transitions, but they may not always fully elucidate their implications for multiple HS dimensions (Koundouri et al., 2024, 2025). Although HS approaches security through an individual-centric lens, it is linked with state security, recognizing the intricate relationships between environmental integrity, socioeconomic stability, and human potential. Hence, it is directly and indirectly impacted by policies and initiatives designed for the state and regional level, as the ones enshrined in the EGD.

This paper proposes a novel, data-driven methodology to systematically assess how European Green Deal policy texts address various Human Security Aspects, including newly acknowledged technological vulnerabilities. By analyzing official EU documents, we demonstrate how advanced semantic modeling can identify thematic alignments or gaps in addressing HS within policies that are explicitly connected to the SDGs. Our approach aims to illuminate both the strengths and the blind spots in current policy discourse, thereby aiding stakeholders in designing interventions that explicitly integrate the human security perspective.

Methodology

The methodological foundation of our study is a semantic text analysis pipeline that measures the degree to which policy documents cover each of the eight Human Security Aspects (economic, food, health, environmental, personal, community, political, and technological). We adopt a transformer-based embedding model to capture contextual and conceptual nuances, avoiding reliance on basic keyword occurrences

alone.

Data preparation and textual descriptors

To build our corpus, we sourced official documents and legislative texts under the umbrella of the European Green Deal. Each text was systematically parsed, cleaned, and segmented into smaller passages, generally one to three paragraphs long, in order to preserve thematic coherence. This segmentation facilitates more accurate semantic comparisons by ensuring that conceptually distinct segments are assessed independently.

We additionally created a curated JSON file representing our main reference framework for HS. Each of the eight Aspects is provided with:

1. A short definition capturing its essence (e.g., "Food Security: access to sufficient, nutritious food")
2. Sub-categories labeled as Material Issues (e.g., "Standard of Living" under Economic Security or "Cybersecurity" under Technological Security)
3. A set of carefully chosen keywords and short descriptive paragraphs that elaborate on each Material Issue (Bajpai, 2000; Commission on Human Security, 2003)

These structured descriptors serve a dual purpose. First, they guide semantic matching by anchoring each Aspect in well-established concepts found in the literature (United Nations Development Programme, 1994). Second, they allow for consistent comparisons across policy texts, mitigating the risk of ad hoc interpretations.

Embedding and similarity calculation

Following segmentation, each text passage is converted into a dense, numerical vector representation—commonly referred to as an embedding. We utilize a Sentence-BERT model (Reimers & Gurevych, 2019), an architecture that fine-tunes the original Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) to produce meaningful sentence- or paragraph-level embeddings.

In parallel, we embed each HS Aspect definition and Material Issue descriptor from the JSON framework. By using a consistent embedding model for both corpus texts and HS Aspects, we can compare them within the same high-dimensional vector space. Cosine similarity (Wang & Cerrato, 2020) then provides a straightforward means to assess thematic alignment: if a segment's embedding closely resembles the embedding of a particular Aspect's descriptor, that segment is deemed to address that Aspect.

This embedding-based approach improves upon simple keyword spotting by recognizing paraphrases or semantically related expressions. Consequently, even if a policy text references health infrastructure without explicitly mentioning the term "health security," the embedding vectors could still yield high similarity scores, thus correctly classifying the segment.

Coverage scoring and normalization

The final step is to consolidate the similarity scores for each HS Aspect and each document. We apply a top-k thresholding approach, retaining only the highest-scoring segments for each Aspect to limit the confounding noise of tangential mentions.

Different values of k (e.g., top 5% or top 10% of segments) can be tested to find a balance between ensuring coverage and avoiding spurious matches.

We then compute an overall coverage measure for each Aspect in each policy text, reflecting the cumulative relevance across top segments. To facilitate cross-document and cross-Aspect comparisons, these coverage figures are normalized so that the sum of all eight Aspects for a single policy is 100%. A more granular level of analysis can examine subtopics (Material Issues), also expressed as a fraction of the total HS coverage in that document.

Visualization and interpretation

Our pipeline automatically generates tabular outputs as well as visual representations (Alkire, 2003). Two primary visualization formats are employed:

1. **Traffic-Light Chart:** Each cell indicates the relative coverage percentage with a three-color scheme (red for low, yellow for medium, green for high). Decision-makers can quickly scan which aspects a particular policy prioritizes or overlooks.
2. **Gradient Heatmap:** A continuous color scale—from light to dark—displays subtle differences in coverage. This allows for more nuanced distinctions even among Aspects that have roughly similar percentage values.

Results and discussion

Applying our semantic analysis to 40 representative European Green Deal documents, we find that coverage of Human Security Aspects is both variable and at times skewed toward certain dimensions. Key observations include:

1. **Economic Security Dominance:** On average, Economic Security registers the highest coverage percentages, hovering around 14%. Many documents focus on financial mechanisms, employment opportunities, and trade aspects, likely due to the Green Deal's emphasis on economic transitions, competitiveness, and green growth. Although this prevalence is encouraging, it also reveals a potential risk of overshadowing other HS dimensions if policies become too concentrated on economic benchmarks.
2. **Food and Community Security:** Food Security (13.6%) and Community Security (13.2%) frequently rank highly, reflecting the Green Deal's focus on agriculture (e.g., Farm to Fork) and social equity (e.g., Just Transition). Such policy emphasis is vital for ensuring affordable, nutritious food as well as inclusive communities resilient to systemic shocks.
3. **Environmental Security Integration:** At approximately 12.9% mean coverage, Environmental Security sits near the midpoint. Many policies engage environmental concerns—climate change mitigation, biodiversity, resource management—but the data show that some documents highlight these more strongly than others.
4. **Health, Personal, and Political Security:** Collectively, these three aspects (Health, Personal, and Political) occupy a middle tier. Policy references to healthcare and well-being (Health Security) appear periodically, but their

distribution is uneven. Personal Security topics, such as protections against violence or disasters, are not always discussed explicitly, although they may be implicitly present in sections on crisis management. Political Security issues vary even more widely, signifying that while certain documents strongly address institutional questions, others emphasize purely technical or environmental considerations.

5. **Lagging Technological Security:** Technological Security averages the lowest coverage (around 10%), even though some policies explicitly mention digital transitions. This disparity suggests a relative lack of direct connections between digital infrastructure and human welfare or rights. Policies focusing on advanced technologies or cybersecurity exist within the Green Deal spectrum but appear less frequently than those on economic or environmental concerns. Future iterations of policy might benefit from explicitly articulating how technologies intersect with broader HS objectives.

Collectively, these patterns suggest that while the EU Green Deal policies often integrate aspects of human well-being, the explicit connection to a comprehensive human security framework remains partial. A holistic EU implementation strategy may, therefore, require additional efforts to ensure that all HS dimensions are systematically addressed.

Conclusion

This research proposes a novel semantic analysis method to systematically map HS Aspects onto policy documents aligned with the SDGs, using the European Green Deal corpus as a test case. The results highlight a strong focus on economic, food, and environmental security, while revealing less consistent coverage of political, personal, and especially technological security. Recognizing these imbalances can inform stakeholders, prompting more targeted interventions in underrepresented areas.

From a methodological standpoint, embedding-based approaches (Sentence-BERT) offer a robust tool for extracting thematic alignment beyond mere keyword overlap. By incorporating definitions and subtopics from a carefully compiled JSON framework, researchers and policy analysts can reliably track whether a given document addresses the substance of an HS dimension, even if the policy text employs different terminology.

Future work may involve integrating these findings into a cross-institutional assessment, contrasting how HS is reflected in national-level legislation versus EU directives. Another avenue would be to link coverage measures with quantitative indicators (e.g., budgets allocated to each security dimension), thereby moving from textual analysis toward more outcome-oriented evaluations. Ultimately, the goal is to ensure that in pursuing sustainable development, policymakers do not neglect the multi-layered security needs of individuals and communities.

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References

- Alkire, S. (2003). A Conceptual Framework for Human Security. Centre for Research on Inequality, Human Security and Ethnicity (CRISE), Working Paper.
- Bajpai, K. (2000). Human Security: Concept and Measurement. *International Journal of Peace Studies*, 5(1), 1–16.
- Commission on Human Security. (2003). *Human Security Now*. New York.
- Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, 4171–4186.
- Koundouri, P., Alamanos, A., Plataniotis, A., Stavridis, C., Perifanos, K., & Devves, S. (2024). Assessing the sustainability of the European Green Deal and its interlinkages with the SDGs. *npj Climate Action*, 3(1), 23, <https://doi.org/10.1038/s44168-024-00104-6>.
- Phoebe Koundouri, Panagiotis-Stavros Aslanidis, Konstantinos Dellis, Angelos Plataniotis, and Georgios Feretzakis. Mapping human security strategies to sustainable development goals: a machine learning approach. *Discover Sustainability*, 6:96, 20.
- Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using Siamese BERT-networks. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 3982–3992.
- United Nations Development Programme. (1994). *Human Development Report 1994*. Oxford University Press.
- Wang, L., & Cerrato, T. (2020). Cosine similarity in text analytics: practical findings. *ACM Transactions on Data Science*, 2(3), 1–22.
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DO WE DO WHAT WE PREACH FOR THE ENVIRONMENT? A PILOT STUDY OF UNIVERSITY SUSTAINABILITY INITIATIVES

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Keywords: Sustainability, university initiatives, SDGs, LLM-augmented text analysis.

Introduction

Sustainable Development has long been a priority on the agenda of higher education institutions (HEIs) (Filho et al. 2024; Gutierrez-Mijares et al. 2023). Over the past decade, HEIs, especially universities, have become major conduits for the teaching and dissemination of United Nations Sustainable Development Goals (SDGs). Universities take substantial efforts to incorporate sustainable practices into their pedagogical approaches, research, and engagement with industry and community. They periodically report their SDG progress to external stakeholders. However, despite these efforts, a key question remains: To what extent do universities align their sustainability initiatives with the SDGs? Do their actions truly reflect their commitments?

This study addresses these questions by applying LLM-augmented text analysis to systematically evaluate university sustainability reports. Unlike traditional approaches such as manual content analysis (González-Torre and Suárez-Serrano 2022) or survey-based studies (Filho et al. 2024), we leverage advanced LLM techniques to analyze sustainability reports at scale. Our methodology employs retrieval augmented generation (RAG) (Lewis et al. 2020) and chain-of-thought prompting (Wei et al. 2022) to classify university initiatives into the 17 SDGs. This automated approach provides a scalable framework for assessing the alignment of university activities with the full spectrum of SDGs. In contrast, existing studies often focus on specific aspects of sustainability, such as case studies (González-Torre and Suárez-Serrano 2022), the integration of SDGs in curricula (Prior et al. 2024), or sustainability-focused research grants (Mohd et al. 2024). These approaches, while valuable, typically examine a limited subset of SDGs—primarily Quality Education (SDG 4) and Partnerships for the Goals (SDG 17).

This LLM-augmented approach allows us to conduct a comprehensive study of university sustainability initiatives in order to:

- Identify the initiatives that universities actually take to support sustainability
- Explore how these initiatives relate to the 17 SDGs
- Understand whether the initiatives universities take to support sustainability are in any way correlated with their characteristics (size, nature, geography, etc.)
- Identify any commonalities or differences across universities
- Identify best practices and explore how they instill a culture of sustainability

- Identify how universities express their support to sustainability, and more.

Data and Method

To achieve these objectives, we undertook a study using the 2023 annual sustainability reports from the top 100 universities in the QS World University Rankings.⁹ These institutions are recognized for their leadership in sustainability, making their reports an ideal dataset for evaluating the best practice in higher education. We collected these reports in PDF or HTML format and extracted text paragraphs. On average, each report contains 41 pages, 207 paragraphs, and 12,277 words.

We developed an LLM-augmented method to classify these paragraphs according to their relevance to SDGs or their lack of relevance (labeled as NoSDG) in three steps. First, we curated a labeled dataset for prompt demonstration and method evaluation. Since several universities have organized their initiatives by SDGs, these initiatives provide us a natural labeled dataset. We collected 845 paragraphs, each associated with a specific SDG. In addition, our research team manually identified 34 paragraphs that were irrelevant to any SDG. From these 879 labeled paragraphs, we randomly select 90, 5 for each label (17 SDGs and NoSDG), to form a demonstration subset, with the rest reserved for out-of-sample testing.

In the second step, we prompted the LLM to reason through the label of each paragraph in the demonstration subset and recorded its chain-of-thought (CoT) traces. An example CoT trace is shown in Appendix 1. The LLM first identified potential SDGs. Then, it retrieved the definitions of these SDGs and assessed the thematic alignment with the paragraph. Finally, the LLM selected the best-matching SDGs or label it as NoSDG based on the alignment.

In the third step, we created a RAG-based CoT prompt template using the demonstration subset. Specifically, for each test paragraph, the template randomly selects two CoT traces that demonstrate how to reason through labels. Additionally, it retrieves the top-5 paragraphs from the demonstration subset that are most semantically similar to the test paragraph. The template combines both the top-5 samples and their labels, along with the CoT traces to form a prompt, which instructs the LLM to classify the test paragraph into SDGs or NoSDGs by referencing the labeled samples and CoT traces.

We tested the prompt on the test dataset of 789 samples and achieved an average of precision and recall of 75% across all labels. Precision measures the percentage of predicted labels that match actual labels, while recall represents the percentage of actual labels retrieved. Table 1 shows examples of classified paragraphs and their labels. Each paragraph in our labelled dataset is assigned to a single SDG. However, many paragraphs are relevant to multiple SDGs (see Example 2 in Table 1), and we instructed the LLM to identify all applicable SDGs. We posited that the absence of certain ground truth labels may account for many of the misclassifications.

To test this conjecture, two researchers independently annotated the misclassified paragraphs with relevant SDGs. The average Kappa score across all labels is 0.72, indicating strong agreement between the annotators. The paragraphs were then updated with the newly agreed-upon labels. Notably, 56 paragraphs were assigned more than one SDG. With the updated labels, our method achieved a precision of

⁹<https://www.topuniversities.com/world-university-rankings>

	Paragraph	SDG on Report	Predicted SDGs
1	We also have a Hazardous Waste Policy that was refreshed in May 2021 , and we provide guidance and posters on wastewater disposal via sinks. Our wastewater is removed and treated by Southern Water.	SDG6	SDG6
2	New 3D Ultrasound May Improve the Accuracy of Liver Cancer Treatment:... The method shows promise in determining whether the entire liver tumor can be effectively ablated by the procedure.	SDG3	SDG3 SDG9

Table 1: Paragraph Classification Examples

0.91, recall of 0.86, and an F1 score of 0.88.

These results exceed the performance of other SDG classification methods (e.g., Sovrano et al. 2020; Yao et al. 2024) and deep learning models on popular multi-label classification benchmarks (Minaee et al. 2021). Overall, this comprehensive prompting technique can effectively identify initiatives aligned with SDGs.

A Pilot Study

We conducted a pilot study by randomly selecting twenty universities, and analyzed their sustainability initiatives, particularly how they align with the SDGs.¹⁰

The findings highlight SDG 13 (Climate Action) as the most frequently addressed initiative, reflecting universities’ strong focus on climate-related policies and projects. Additionally, SDG 4 (Quality Education) ranks second, emphasizing the essential role of universities in advancing education, research, and knowledge dissemination as part of their sustainability efforts.

The study also reveals differences between public vs. private and technical vs. comprehensive universities. Private universities focus more on SDG 8 (Decent Work and Economic Growth) than public institutions, suggesting a stronger emphasis on workforce development, economic initiatives, and industry collaborations. Meanwhile, compared to comprehensive universities, technical universities prioritize SDG 13 (Climate Action), likely due to their focus on technological advancements and scientific solutions for sustainability. Comprehensive universities, in contrast, place greater emphasis on SDG 4 (Quality Education), reinforcing their broader academic and societal mission.

Institutional and geographical differences also influence sustainability priorities. Some universities emphasize social sustainability goals such as SDG 10 (Reduced Inequalities), while others focus on technological and industrial advancements related

¹⁰The universities analyzed are University of Toronto, UC Berkeley, University of Manchester, University of British Columbia, Imperial College London, Massachusetts Institute of Technology (MIT), New York University, Technical University of Munich, University of Cologne, University of Southampton, Pennsylvania State University, Arizona State University, University College Dublin, Aalto University, University of Alberta, Lund University, University of Calgary, University of Waterloo, Wageningen University & Research, and University of St Andrews.

to SDG 9 (Industry, Innovation, and Infrastructure). Additionally, top-ranked universities tend to have more balanced SDG coverage, while lower-ranked universities often concentrate on a few select SDGs.

Overall, the findings confirm that SDG 13 and SDG 4 are the two dominant themes in university sustainability initiatives. However, institutional type, funding model, and academic focus shape key differences in SDG prioritization. These insights provide a strong foundation for further research, particularly in identifying gaps in sustainability initiatives and exploring strategies to achieve a more comprehensive SDG alignment across higher education institutions.

Conclusion

This study underscores the importance of universities in advancing sustainability efforts and their alignment with the SDGs. Our preliminary findings reveal that institutional characteristics such as size, reputation, and focus areas play a critical role in shaping sustainability strategies. Moreover, our study demonstrates the potential of LLM-powered approaches to enhance sustainability research. It suggests that AI tools, like LLMs, can be valuable assets for large-scale sustainability research, while still requiring human expertise for more nuanced classification and evaluation. Our methodology provides a scalable, data-driven framework for evaluating institutional sustainability efforts at a global level, offering actionable insights for universities seeking to strengthen their contributions to the UN SDGs.

References

- Amoros Molina, A., Hellden, D., Alfven, T., Niemi, M., Leander, K., Nordenstedt, H., Rehn, C., Ndejjo, R., Wanyenze, R. and Biermann, O., 2023. Integrating the United Nations sustainable development goals into higher education globally: a scoping review. *Global Health Action*, 16(1), p.2190649.
- Filho, W.L., Sierra, J., Price, E., Eustachio, J.H.P.P., Novikau, A., Kirrane, M., Dinis, M.A.P. and Salvia, A.L., 2024. The role of universities in accelerating the sustainable development goals in Europe. *Scientific reports*, 14(1), p.15464.
- González-Torre, P.L. and Suárez-Serrano, E., 2022. A framework for implementing and reporting United Nations sustainable development goals in Spanish higher education institutions. *International Journal of Sustainability in Higher Education*, 23(6), pp.1349-1365.
- Gutierrez-Mijares, M.E., Josa, I., Casanovas-Rubio, M.D.M. and Aguado, A., 2023. Methods for assessing sustainability performance at higher education institutions: a review. *Studies in Higher Education*, 48(8), pp.1137-1158.
- Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W.T., Rocktäschel, T. and Riedel, S., 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33, pp.9459-9474.
- Minaee, S., Kalchbrenner, N., Cambria, E., Nikzad, N., Chenaghlu, M. and Gao, J., 2021. Deep learning-based text classification: a comprehensive review. *ACM computing surveys (CSUR)*, 54(3), pp.1-40.
- Mohd, S., Abdul Latiff, A.R. and Syed Azhar, S.N.F., 2024. Research Impact Assessment on Sustainable Development Goals in Higher Education Institutions: A

Qualitative Study. SAGE Open, 14(3), p.21582440241281095.

Prior, D.D., Mysore Seshadrinath, S., Zhang, M. and McCormack, M., 2024. Measuring sustainable development goals (SDGs) in higher education through semantic matching. Studies in Higher Education, pp.1-14.

Sovrano, F., Palmirani, M. and Vitali, F., 2020, September. Deep learning based multi-label text classification of UNGA resolutions. In Proceedings of the 13th international conference on theory and practice of electronic governance (pp. 686-695).

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E., Le, Q.V. and Zhou, D., 2022. Chain-of-thought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35, pp.24824-24837.

Yao, R., Tian, M., Lei, C.U. and Chiu, D.K., 2024. Assigning multiple labels of sustainable development goals to open educational resources for sustainability education. Education and Information Technologies, pp.1-23.

Appendix 1: Example of Chain-of-Thought

Given the paragraph below:

In February 2023, 75 Massey staff members completed almost 1,000 rides for Love to Ride's 2023 Aotearoa Bike Challenge. Additionally, a new bike and scooter storage area for students and staff was opened on the Wellington campus. This was made possible with support from the Wellington City Council.

Which SDGs are best aligned with it?

A: Let's solve this problem step by step.

Step 1: Find candidate SDGs that are relevant to the themes of this paragraph. This paragraph is relevant to SDG 11, SDG 3, SDG 13

Step 2: Retrieve the definitions of these candidate SDGs

- SDG 3 (Good Health and Well-being): Ensure healthy lives and promote well-being for all at all ages.
- SDG 11 (Sustainable Cities and Communities): Make cities and human settlements inclusive, safe, resilient, and sustainable.
- SDG 13 (Climate Action): Take urgent action to combat climate change and its impacts.

Step 3: Based on the definitions, determine which SDGs can best characterize the themes of the paragraph.

SDG 11: Sustainable Cities and Communities

Reason: The paragraph focuses on actions that contribute to making the campus environment more sustainable by promoting cycling (a more

eco-friendly mode of transport) and improving infrastructure (bike and scooter storage area). This directly aligns with SDG 11, ...

Although SDG 3 and SDG 13 are also relevant, SDG 11 is the most closely aligned because the paragraph specifically highlights urban infrastructure changes and the promotion of sustainable transportation within a community.

Finish: [SDG 11]

LEVERAGING AI FOR ESG ADVANCEMENT IN GREEN HOTELS: EXPLORING SUSTAINABILITY, INNOVATION AND CHALLENGES

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Keywords: AI, green hotels, ESG, SDGs, Greece.

Abstract

In our fast-changing world, the convergence of technology and sustainability has become increasingly crucial. The environmental, social, and governance (ESG) movement encompasses crucial issues related to the environment (such as climate change, waste management, and water resources), social aspects (including diversity, equity, inclusion, education, and well-being), and governance (like corporate structure, transparency, and compensation systems). These issues are vital for the welfare of all business stakeholders. Since the hospitality and tourism sector relies significantly on natural resources and human capital, it is crucial to implement ESG practices. These practices help develop efficient food waste management systems, boost community involvement, and guarantee the equitable treatment of employees (Back, i-Joon, 2024). Regrettably, as Legendre et al. (2024) reveal in their bibliometric analysis of hospitality and tourism literature, current ESG literature is plagued by inconsistent conceptualizations, measurements, and reporting frameworks. Thus, Back, i-Joon, (2024) underscore to mitigate these inconsistencies, additional ESG research should be undertaken through collective and collaborative efforts to better comprehend societal needs.

As we enter a pivotal era ESG advancements, artificial intelligence (AI) is emerging as a powerful tool that has the potential to revolutionize the approach to sustainability and responsible investing (Abdalmuttaleb et al. 2022; Lim, 2024; Stanley 2023). This cutting-edge technology excels at analyzing extensive datasets, making insightful predictions, and automating intricate decision-making processes, thereby providing businesses with remarkable opportunities to foster significant positive change. The application of AI in ESG initiatives offers new opportunities for organizations to enhance their understanding, analysis, and implementation of sustainable practices (Velidor, 2023). While acknowledging the widespread recognition of AI's potential in achieving sustainable development, there remains a notable deficiency and thorough examination of its specific applications, impacts, and challenges, particularly within the hospitality industry (Kasavana & Davis, 2019; Knani et al. 2022; Limna, 2023; Nam et al., 2021; Nikopoulou et al., 2023). Drawing on theoretical frameworks such as the Diffusion of Innovation (technological innovation), the Technology-Organization-Environment (TOE), and the Triple Bottom Line (TBL), this study aims to explore the adoption of AI technologies by green hotels in Greece to support ESG initiatives and advance progress towards the United Nations Sustainable Development Goals (SDGs). Given the relatively unresearched nature of this topic (Ivanof et al., 2020), the research questions are: How do green hotels in Greece utilize AI to support ESG initiatives, and what challenges do they face in adopting AI?

This exploratory research employs a mixed-methods approach, combining case studies and surveys for a thorough analysis. We surveyed 100 randomly selected Green Hotels from a list of 360 in Greece. 20 Managers/owners decided to participate in a 50-minute interview. Additionally, we conducted case studies involving interviews with 4 hoteliers. The research aims to:

- Identify AI techniques used by Green Hotels to support ESG and specific SDGs (case studies)
- Analyze challenges and issues related to AI implementation in Green Hotels (case studies and survey)
- Explore current and future AI trends for advancing UN SDGs in the hospitality industry (survey and case study)

This study significantly contributes to the literature by addressing gaps in understanding the impacts of digital transformation, particularly AI adoption, in the hospitality industry, with a focus on voluntary green initiatives like the Green Key certification. By examining the relationship between institutional forces, such as regulatory and stakeholder pressures, and proactive environmental behavior in Green Hotels. This research seeks to provide valuable insights into the role of AI in enhancing sustainability practices and achieving SDGs. The findings of this study will undoubtedly enrich our understanding and potentially guide future research in this critical area.

Findings

Our study revealed distinct patterns in AI adoption across different hotel sizes:

- **Small Hotels (Up to 100 Beds):** Focus on basic resource management and energy efficiency. Examples: Thessaloniki (Energy management), Cyclades (Resource management)
- **Medium Hotels (101-500 Beds):** Emphasis on more comprehensive resource and waste management. Examples: Kruopigi (Supply chain optimization, waste management), Stalida / Hersonissos (Energy and water management)
- **Large Hotels (501-1000 Beds):** Greater focus on guest and staff engagement in sustainability practices. Example: Ialysos (Communication systems for sustainability practices)
- **Very Large Hotels (Over 1000 Beds):** General sustainability efforts, with potential for future AI implementations. Example: Rethymno / Mylopotamos (General sustainability efforts)

Location-Specific Observations: Hotels in coastal and tourist-heavy areas (like Crete and Halkidiki) often emphasize energy and waste management, aligning with SDGs related to responsible consumption, clean energy, and climate action. This comparison highlights how hotel size and location influence the implementation of AI

techniques and their alignment with ESG goals. Larger hotels and those in popular tourist destinations tend to have more comprehensive and advanced sustainability practices, potentially due to higher resources and guest expectations.

Additionally, data shows the technical skills required for AI adoption in hotels, grouped by their size:

- **Small hotels (0-100 beds):** Primarily require basic computer skills, data management, and security, though some lack awareness of specific AI needs
- **Medium-sized hotels (100-300 beds):** Emphasize data analysis, AI technology integration, and marketing strategies
- **Large hotels (300-500 beds):** Demand more advanced competencies, including AI algorithm development, performance evaluation, and data management
- **Very large hotels (500+ beds):** Require expertise in machine learning, cloud computing, NLP, and comprehensive data security, along with staff training for AI implementation

Data highlights the progression of technical skill requirements from basic data management in small hotels to advanced AI-specific skills in very large hotels.

Conclusion

Our study explored the adoption of AI technologies in Green Hotels in Greece, examining their contributions to ESG initiatives and alignment with SDGs. The findings indicate a strong focus on energy management, resource optimization, and waste reduction, particularly in tourist-heavy regions. However, challenges such as integration with existing systems, lack of specialized knowledge, and regulatory compliance were identified. Effective leadership, staff training, and change management are crucial for overcoming these obstacles. Additionally, the study highlights that smaller hotels often require more support in adopting advanced AI technologies compared to larger establishments. In conclusion, integrating ESG principles into hotel management not only enhances operational efficiency and cost-effectiveness but also strengthens brand reputation, fosters stakeholder trust, and positions hotels as leaders in sustainable hospitality practices. This holistic approach is increasingly recognized as essential for long-term success in the hospitality industry.

To enhance understanding of AI's impact on sustainability in hospitality, future research should focus on:

- **Sample Size and Diversity:** Include a larger and more diverse range of hotels and regions
- **Longitudinal Studies:** Examine long-term effects of AI on sustainability and financial performance
- **Qualitative Insights:** Gather stakeholder perspectives through interviews and focus groups

- **Technology and Market Trends:** Analyze current advancements and trends to identify best practices
- **Cost-Benefit Analysis:** Evaluate the financial aspects of AI adoption, including costs and returns
- **Regulatory Impact:** Investigate how regulations affect AI implementation, focusing on data management and compliance

These approaches will offer a thorough view of AI's role in sustainable development within the hospitality industry.

References

Abdalmuttaleb MA, Al-Sartawi M, Hussainey K, Razzaque A (2022) The role of artificial intelligence in sustainable finance. *J Sustain Fin Invest.* <https://doi.org/10.1080/20430795.2022.2057405>

Back, i-Joon. "ESG for the Hospitality and Tourism Research: Essential Demanded Research Area for All." *Tourism Management* 105 (2024): 104954. ISSN 0261-5177. <https://doi.org/10.1016/j.tourman.2024.104954>.

Božić, Velibor. (2023). ENVIRONMENTAL, SOCIAL, AND GOVERNANCE APPROACH (ESG) & ARTIFICIAL INTELLIGENCE (AI). 10.13140/RG.2.2.34753.12641.

Kasavana, M.L.; Davis, J. Artificial Intelligence and the Hospitality Industry: Perspectives on the Past, Present, and Future. *Cornell Hosp. Q.* 2019, 60, 136-144

Khlyusevich, A., Inversini, A., Schegg, R. (2024). Artificial Intelligence and Hospitality: A Challenging Relationship. In: Berezina, K., Nixon, L., Tuomi, A. (eds) *Information and Communication Technologies in Tourism 2024*. ENTER 2024. Springer Proceedings in Business and Economics. Springer, Cham. https://doi.org/10.1007/978-3-031-58839-6_27

Knani, M.; Echchakoui, S.; Ladhari, R. Artificial intelligence in tourism and hospitality: Bibliometric analysis and research agenda. *Int. J. Hosp. Manag.* 2022, 107, 103317.

Legendre, T.S., A. Ding, and K.J. Back. "A Bibliometric Analysis of the Hospitality and Tourism Environmental, Social, and Governance (ESG) Literature." *Journal of Hospitality and Tourism Management* 58 (2024): 309-321. <https://doi.org/10.1016/j.jhtm.2024.01.00>.

Lim, T. Environmental, social, and governance (ESG) and artificial intelligence in finance: State-of-the-art and research takeaways. *Artif Intell Rev* 57, 76 (2024). <https://doi.org/10.1007/s10462-024-10708-3>

Limna, P. (2023). Artificial Intelligence (AI) in the hospitality industry: A review article. *International Journal of Computing Sciences Research*, 7, 1306-1317. <https://doi.org/10.25147/ijcsr.2017.001.1.103>

Nam, K., Dutt, C.S., Chathoth, P., Daghfous, A., Khan, M.S.: The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges. *Electron Mark.* 31, 553-574 (2021). <https://doi.org/10.1007/s12525-020-00442-3>

Nikopoulou, M., Kourouthanassis, P., Chasapi, G., Pateli, A., Mylonas, N.: Determinants of digital transformation in the hospitality industry: technological, organizational, and environmental drivers. *Sustainability* 15, 2736 (2023). <https://doi.org/10.3390/su15032736>

Stanley M (2023) How AI can bolster sustainable investing. Institute for sustainable investing, Morgan Stanley. <https://www.morganstanley.com/ideas/ai-sustainable-investing-use-potential>.

Session A6

LEADERSHIP DEVELOPMENT IN THE AGE OF AI A Panel Roundtable Discussion

Chair: Peter Dominick, Stevens Institute of Technology, USA

LEADERSHIP DEVELOPMENT IN THE AGE OF AI

A Panel Roundtable Discussion

Moderator:

- **Dr. Peter Dominick**, Industry Professor, Director of Stevens' Technical Leadership Executive Education Program and Co-Director of the Inclusive Leadership Certificate Program, Stevens Institute of Technology.

Panel members:

1. **Dr. Joanna Eugenia Bakoumi**, L&D Manager at Maersk Training and Academic Course Director at Lloyd's Maritime Academy.
2. **Ms. Georgia Malamateniou**, Country HR Director, Greece & Cyprus, Schneider Electric.
3. **Mr. Vassilis Chouliaras**, HR Director Eastern Europe, Turkey, Middle East and Africa at Barilla Group.

Abstract:

Even in the age of artificial intelligence (AI), for the foreseeable future, organizational life will still revolve around working with, through and for others. That fact assures that effective leadership and the need to develop leaders will remain integral to organizational success. Nonetheless, rapid advancements in artificial intelligence have ushered in opportunities to reimagine, transform and accelerate how leadership development occurs. Examples include its implications for personalizing development paths, enriching reflection and self-awareness, enhancing interpersonal skills, identifying potential and reducing development costs. At the same time, AI's role in leadership development also presents challenges that include depersonalizing development, data privacy considerations and concerns about bias and undermining inclusion.

This panel discussion aims to explore these as well as related possibilities and challenges. We also intend to shed light on the current state of practice when it comes to utilizing AI for leadership development. The panel will consist of professionals currently engaged in leadership development work as training professionals, coaches and human resources practitioners. It is worth noting too that related academic research is in its nascent stages and we hope the ensuing panel conversation can serve as a springboard to encourage future research. Key themes and questions that will be the focus of discussion include:

- **AI as a Tool for Leadership Development:** How can AI-powered tools and platforms be used to enhance leadership development programs? What are the potential benefits and limitations?
- **Ethical Considerations and Responsible AI:** What are the ethical implications of using AI in leadership development? How can we ensure fairness, transparency, and accountability?

- **The Human Element in Leadership:** How can we balance the use of AI with the essential human aspects of leadership, such as empathy, emotional intelligence, and critical thinking?
 - **The Evolving Landscape of Leadership in the Age of AI:** How is AI changing the skills and competencies required for effective leadership? What new challenges and opportunities are emerging?
 - **The Future of Leadership Development:** What are the long-term implications of AI for the field of leadership development? How can we prepare future leaders for an AI-driven world?
-

Session B6

**SOCIAL MEDIA AND
USER EXPERIENCE**

Chair: Michael Tsiros, University of Miami, USA

THE SMARTPHONE INTUITION: HOW SMARTPHONE USE DECREASES DECISION-MAKING CONFIDENCE

Michael Tsiros, Vincentia Yuen, Claudia Townsend
University of Miami

Keywords: Smartphone, consumer intuition, consumer behavior, consumer technology interaction.

Consumers increasingly rely on smartphones for numerous daily activities that previously were performed on personal computers (PCs). Despite the widespread usage of smartphones, certain decisions (e.g., purchasing, investing), still tend to occur more frequently on PCs. Thus, understanding the effects of smartphone use on decision-making becomes crucial for optimizing smartphone conversion rates. This research explores how, when, and why smartphone use influences decision-making.

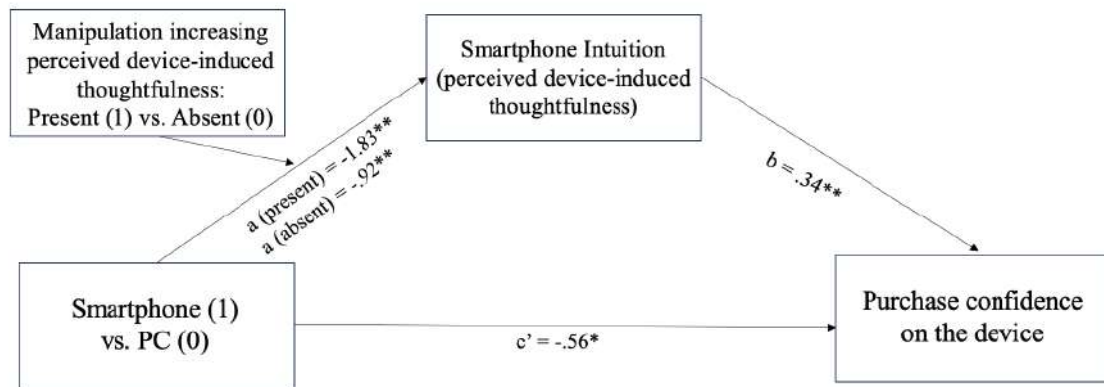
Our research reveals that consumers intuitively believe that using smartphones (vs. PCs) induces lower levels of thoughtfulness. This intuition is based on their personal experiences and observations of how tasks are performed on each device. The differences in device size (Ghose, Goldfarb, & Han, 2013), the association of tasks performed on each device (e.g., socializing and entertainment vs. work-related tasks; Melumad & Meyer, 2020), and the typical situational usage patterns associated with smartphones versus PCs (e.g., on the go, in public; Rainie & Zickuhr, 2015) contribute to this belief. As consumers often seek cause-and-effect relationships and attribute failures to external factors (Clary & Tesser, 1983), they view these correlations and intuitively believe that using a smartphone (vs. PC) induces lower thoughtfulness. A pilot study supports this hypothesis (Table 1).

Furthermore, because consumers believe that careful thought leads to better judgments (Barden & Petty, 2008), this smartphone intuition leads consumers to be less confident in their decision-making when using a smartphone (vs. PC). Hence, holding all else constant, including user demographics, location, goal, input interface, and screen size, consumers are less likely to engage in some decision-making tasks on a smartphone (vs. PC). This effect can persist even when actual performance on a smartphone (vs. PC) is equal or superior. Formally:

- H1: Smartphone (vs. PC) use decreases consumers' perceived induced thoughtfulness in their decision-making.
- H2: Smartphone (vs. PC) use decreases consumers' decision-making confidence.
- H3: Consumers' lower perceived induced thoughtfulness in their decision-making on smartphones (vs. PCs) mediates the relationship between device use and decision-making confidence on the device.

We examine these hypotheses in four studies with four replications (Table 2) involving random assignment to device (smartphone vs. PC; except study 3) and all using 7-point scales.

Participants completed two studies (order counterbalanced): (1) a product evaluation study and (2) an electronic devices study. For (1), after seeing the product



Note: The path coefficients are unstandardized betas. * $p \leq .01$ ** $p \leq .001$.

Figure 1

information, participants rated their confidence in making a decision to purchase a cruise package. For (2), we measured general perceptions of the device, perceived induced thoughtfulness and alternative accounts (e.g., privacy concerns). As predicted, participants intuit that using a smartphone makes their decision-making less thoughtful ($M = 4.04$) than PC use ($M = 5.71$; $t(241.56) = 10.18$, $p < .001$). Smartphone participants were less confident than PC participants ($M_{\text{Smartphone}} = 4.13$ vs. $M_{\text{PC}} = 4.95$; $t(262.04) = 4.00$, $p < .001$), which is mediated by perceived induced thoughtfulness ($\beta = -.71$; -1.0263 to -0.4276), and not mediated by any alternative accounts. Studies 1B-1D replicated the findings in financial, tangible, and health product contexts while controlling for touchscreen use and screen size, respectively.

Participants were randomly assigned to one of four conditions in a between-subjects design: device (smartphone vs. PC) and intervention presence (control vs. present). The only distinction between control and intervention conditions is the presence of an article explaining how people can be thoughtful on smartphones [PCs]. Participants completed two studies similar to study 1 though about earbud purchase. An ANOVA on confidence revealed only a main effect of device type ($p < .001$) and an interaction with intervention presence ($p = .058$). In the control, participants on smartphones ($M = 4.48$) were less confident in their purchase decision than those on PCs ($M = 5.82$, $F(1, 335) = 34.65$, $p < .001$, $\eta^2 = .094$). This device effect was diminished in the intervention conditions ($M_{\text{Smartphone}} = 4.99$ vs. $M_{\text{PC}} = 5.71$; $F(1, 335) = 10.36$, $p = .001$, $\eta^2 = .030$). The presence of the intervention increased confidence among those on smartphones ($M_{\text{present}} = 4.99$ vs. $M_{\text{control}} = 4.48$; $F(1, 335) = 4.39$, $p = .037$) but not among those on PCs ($M_{\text{present}} = 5.82$ vs. $M_{\text{control}} = 5.71$; $F(1, 335) = .237$, $p = .63$). A mediation analysis (Hayes, 2018; Model 7) indicated moderated mediation (index = .32; .1173 to .5621).

Study 3 analyzed sales data from a retailer offering two types of products: consumer- and concierge-selection. The latter outsources decision-making thus reducing perceived thought needed (pretest confirmed). We hypothesized that lower smartphone decision-making confidence (vs. PCs) could be mitigated by reducing perceived thought for purchase through product type. A binary logistic regression analysis on purchase revealed main effects of device type ($p < .001$) and product type ($p < .001$), and an interaction ($p < .001$). The conversion rate on smartphones

(1.89%) was lower than that on PCs (3.31%; $\chi^2(1, 23, 631) = 39.76, p < .001$). While the rate on smartphones (vs. PCs) of purchasing customer selection products (control) was lower (Smartphone = 7.86%, PC = 30.88%; $\chi^2(1, 1, 425) = 96.67, p < .001$, Cramer's $V = .26$), the device effect was weakened when consumers purchased concierge selection products (Smartphone = 1.46%, PC = 2.23%; $\chi^2(1, 22, 206) = 15.18, p < .001$, Cramer's $V = .026$).

In addition to purchase confidence, Study 4A examined the accuracy and thus the potential overgeneralization of smartphone intuition. Participants predicted their performance on an eight-question evaluation and choice task using the earbud information from Study 2. They also had the chance to make a real choice from the provided options. Participants on smartphones performed the task better than those on a PC ($M_{\text{Smartphone}} = 6.85, M_{\text{PC}} = 6.13, t(281.41) = 2.81, p = .005$). Despite this, those on smartphones (vs. PCs) had lower purchase confidence ($M_{\text{Smartphone}} = 4.87, M_{\text{PC}} = 5.24, t(284) = 2.15, p = .032$), predicted lower performance ($M_{\text{Smartphone}} = 4.93, M_{\text{PC}} = 5.53, t(285) = 2.65, p = .009$; Figure 2), and were less likely to choose (72.22% vs. 82.50%; $\chi^2(1, 287) = 4.34, p = .037$). Study 4B replicated this in the health product contexts.

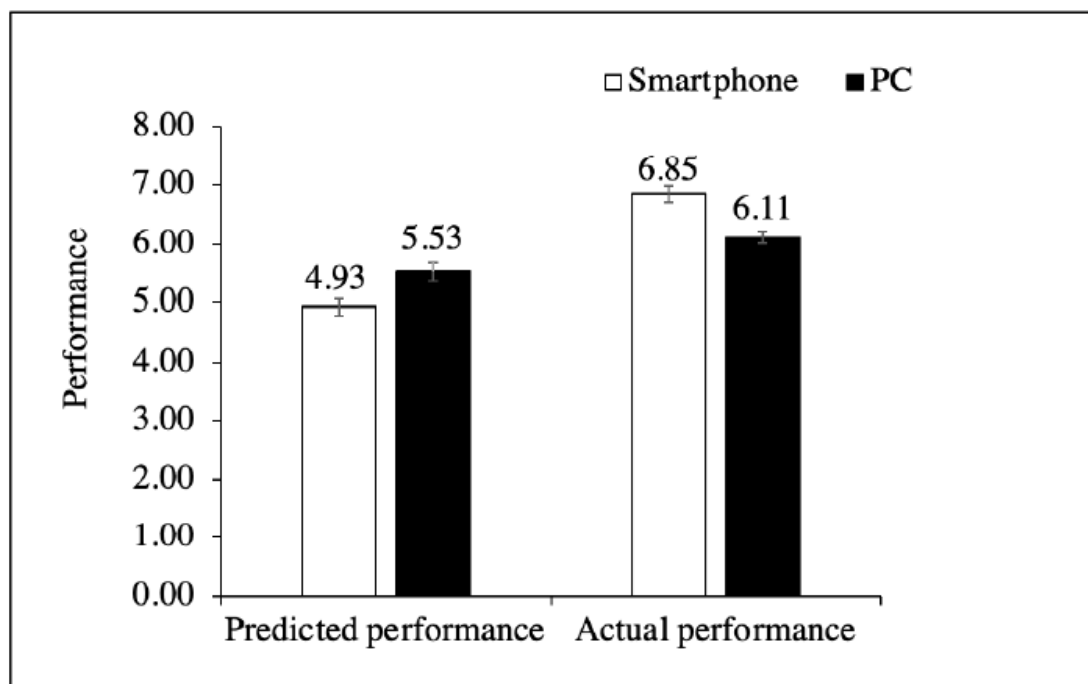


Figure 2

Our findings provide direct evidence of a specific cause of differences in consumer decision-making confidence across device types, offering valuable theoretical and managerial insights into mobile marketing.

Source (1 = “not at all”; 7 = “to a great extent”)	Mean	SD	t-test vs. scale midpoint	Correlations with Smartphone Intuition
Device size	4.89	1.71	9.37***	.336***
Common tasks completed on devices	4.61	1.67	6.55***	.223***
Usage situations of the devices	4.86	1.69	9.19***	.123*
Intimate personal information contained on the device	4.07	1.93	.663 ^{n.s.}	.001 ^{n.s.}
Comforting feelings using the devices	4.12	1.77	1.26 ^{n.s.}	-.065 ^{n.s.}

* $p < .05$, ** $p < .01$, *** $p < .001$, n.s. = not significant.

Table 1: Sources of Smartphone Intuition

Study N Population, Context	Conditions	Dependent Variables	Smartphone Control (Intervention)	PC Control (Intervention)	Main effect	Interaction effect	Mediation via Intuition	Control factors	Hypotheses
Study 1A, 307 CloudResearch workers, Experiential product	2 Device (smartphone vs. PC)	Smartphone intuition [thoughtfulness]	4.04	5.71	$p < .001$	/	/	Demographics, goals	Support H1
		Purchase decision confidence	4.13	4.95	$p < .001$	/	95% CI, -1.0263 to -.4276		Support H2 and H3
Study 1B, 299 MTurk workers, Financial products	2 Device (smartphone vs. PC)	Smartphone intuition [thoughtfulness]	4.19	5.88	$p < .001$	/	/	Demographics, goals	Support H1
		Confidence in opening an account	3.93	4.41	$p = .02$	/	95% CI, -.9676 to -.4051		Support H2 and H3
Study 1C, 459 undergraduates, Tangible products	2 Device (smartphone vs. PC)	Smartphone intuition [thoughtfulness]	3.31	5.00	$p < .001$	/	/	Input interface (i.e., touchscreen), location demographics, goals, location	Support H1
		Purchase decision confidence	4.45	4.77	$p = .031$	/	95% CI, -.4798 to -.0739		Support H2 and H3
Study 1D, 254 undergraduates, Health products	2 Device (smartphone vs. PC)	Smartphone intuition [thoughtfulness]	3.37	3.85	$p < .001$	/	/	Screen size, location demographics, goals	Support H1
		Purchase decision confidence	4.96	4.30	$p = .021$	/	90% CI, -.1552 to -.1971		Support H2 and H3
Study 2, 339 CloudResearch workers,	2 Device (smartphone vs. PC) x 2 intuition manipulation (absent vs. present)	Smartphone intuition [thoughtfulness]	3.91 (4.88)	5.74 (5.80)	$p < .001$	$p < .001$	/	Demographics, goals	Support H1, H2, and H3
		Purchase decision confidence	4.48 (4.99)	5.82 (5.71)	$p < .001$	$p = .058$	95% CI, -.9034 to -.3850 (-.5014 to -.1622)		
Study 3, 23,631 Online customers secondary data, Product purchase	2 Device (smartphone vs. PC) X Product type (customer selection vs. concierge selection)	Actual purchase	7.86% (1.46%)	30.88% (2.23%)	$p < .001$ ($p < .001$)	$p < .001$	/	/	Support H2
Study 4A, 286 MTurk workers, Tangible products	2 Device (smartphone vs. PC)	Purchase confidence	4.87	5.24	$p = .032$	/	/	Demographics, goals	Support H2
		Predicted performance	4.93	5.53	$p = .009$				
		Conversion rate	72.22%	82.50%	$p = .037$				
		Actual performance	6.85	6.13	$p = .005$				
Study 4B, 296 MTurk workers, Dental insurance plans	2 Device (smartphone vs. PC)	Purchase confidence	4.51	5.13	$p = .001$	/	/	Demographics, goals	Support H2
		Predicted performance	4.88	5.48	$p = .01$				
		Conversion rate	74.26%	88.75%	$p = .001$				
		Actual performance	5.94	5.56	N.S.				

Table 2: Summary of studies (and replications)

References

Barden, J., & Petty, R. E. (2008). The mere perception of elaboration creates attitude certainty: exploring the thoughtfulness heuristic. *Journal of personality and social psychology*, 95(3), 489.

Clary, E. G., & Tesser, A. (1983). Reactions to unexpected events: The naive scientist and interpretive activity. *Personality and Social Psychology Bulletin*, 9(4), 609-620.

Ghose, A., Goldfarb, A., & Han, S. P. (2013). How is the mobile Internet different? Search costs and local activities. *Information Systems Research*, 24(3), 613-631.

Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford publications.

Rainie, L., & Zickuhr, K. (2015). Americans' views on mobile etiquette. Pew Research Center: Internet, Science & Tech. <https://www.pewresearch.org/internet/2015/08/26/americans-views-on-mobile-etiquette/>

Melumad, S., & Meyer, R. (2020). Full disclosure: How smartphones enhance consumer self-disclosure. *Journal of Marketing*, 84(3), 28-45.

ASYMMETRIC EFFECTS OF SERVICE ATTRIBUTES ON TRAVELER SATISFACTION WITH SEMI-SUPERVISED TOPIC MODELLING

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Keywords: Online reviews, hotels, topic modelling, asymmetric effects.

Understanding the factors of traveller satisfaction is essential for hospitality industry companies aiming to sustain a competitive advantage and broaden their customer base. Traditional methods, like SERVQUAL (Parasuraman et al., 1988), assume a linear and symmetrical relationship between service attributes and traveller (customer) satisfaction. However, recent studies suggest the existence of asymmetric effects governing the relationship with important implications for business. Enhancing selected service attributes could greatly increase traveller satisfaction, whereas their lack might not proportionally decrease it, and vice versa. The presence of asymmetry underscores the necessity for advanced analytical techniques to understand the intricate interaction between service elements and customer perceptions.

The last decade, a research stream emerged focusing on the asymmetric relationship between traveller satisfaction and service attributes (Albayrak and Caber, 2015; Bi et al., 2020). In a recent study, Albayrak et al. (2024) using a questionnaire as data collection instrument investigated the asymmetric relationships between service quality attributes and customer engagement, extending to this respect the classical traveller satisfaction, for five-star chain hotel, located in Antalya, Türkiye and confirmed the principle of three factor theory. Likewise, Bui and Robinson (2024) examined the asymmetric effects of all-inclusive holiday service quality attributes on traveller satisfaction using Netnography followed by on-line survey and examined asymmetric effects with multiple approaches. In the context of shopping tourism, Lee and Choi (2020) explored the asymmetric effects of shopping destination attributes on overall satisfaction using mix-methods. Guo et al. (2017) combined studied asymmetric effects using Latent Dirichlet Allocation to analyse online reviews across different countries and found 19 factors critical for managing traveling satisfaction and stressed the importance of understanding the asymmetric effects of the service attributes. On the one hand, these studies highlight the necessity for hotel managers to recognize the asymmetric nature of service attributes and on the other depict the research opportunities of the hospitality industry because of the existence of various interconnected factors reflecting social behaviour.

Three-factor theory of customer satisfaction provides lens to thoroughly study asymmetric effects and help managers to prioritize resources and corrective actions. According to this theory, service attributes are categorized in three distinct categories which are: (i) Basic factors are service attributes that lead to dissatisfaction when poorly delivered, but their adequate presence does not significantly enhance satisfaction, (ii) Performance factors that their deliver (or lack) proportionally affects traveller's satisfaction and (iii) Excitement factors. For instance, ensuring that basic factors meet guest expectations can prevent dissatisfaction, while investing in excitement factors can create memorable experiences that significantly

boost satisfaction. Martilla and James (1977) suggested Importance-Performance Analysis (IPA) to evaluate the relative importance of service attributes, Matzler et al. (2003) suggested an improved version of IPA by proposing unequal impact on satisfaction from positive and negative deviations, and Penalty-Reward Contrast Analysis (PRCA) that distinguished penalty effects (attributes causing dissatisfaction) and reward effects (attributes increase satisfaction) (Brandt, 1988). These models are considered as service marketing models used to quantify the asymmetric effects and it is commonly adopted in conjunction with the three-theory factor.

The objective of this work is to explore the asymmetric effects of service attributes on traveller satisfaction by exploiting text sources. We selected to analyse the asymmetric effect of service attributes on traveller satisfaction by utilizing on-line reviews. A semi-supervised topic modelling (Seeded Latent Dirichlet Allocation - SLDA) (Watanabe and Baturu, 2024) approach selected to automatically extract service attributes from on-line reviews and map into predefined aspects followed by PRCA. This work differentiates from previous studies in two respects. First, it combines topic modelling for the service feature extraction with PRCA to quantify the asymmetric effects of service attributes on traveller satisfaction. Second, it employs predefined topics (aspects) namely (i) Location (ii) Personnel (iii) Food (iv) Cleanliness (v) Comfort (vi) Facilities (vii) Room (viii) Price and (ix) Service processes in accordance with the suggestions of Guo et al. (2017) for topic modelling to ensure the interpretability of results.

This study employs a data driven approach to analyse traveller satisfaction through text mining and statistical modelling. Our theoretical framework posits that nine performance attributes asymmetrically influence tourism satisfaction. The methodology follows an iterative process, beginning with comprehensive data collection from the Booking.com platform, encompassing reviews from six Greek destinations with a focus on three-star and higher-rated hotels over a three-year period. All reviews were translated into English, maintaining the platform's distinct structure of positive and negative feedback corpora.

The data preprocessing phase implemented rigorous quality control to ensure data integrity. This included systematic removal of duplicates, text validation, and spelling correction procedures. The text processing protocol incorporated word tokenization, case normalization, and careful filtering of numerical content and punctuation. We eliminated common stop-words and context-specific terms while validating character length to maintain data quality.

For the topic modelling hyperparameter tuning, we implemented SLDA, an enhancement of traditional LDA, as described by Watanabe and Baturu (2024). The model configuration utilized carefully selected hyperparameters: an α value of 0.5 to control document-topic distribution, β set to 0.1 for word-topic association strength, and γ at 0 to eliminate inter-sentence topic transition effects. This configuration reflects the typically concise nature of hotel reviews while maintaining interpretive topic differentiation. The seed selection process involved expert review of the hundred most frequent terms, with five-word seeds chosen for each of the nine predefined service attributes.

Given that our framework identifies nine distinct service attributes, and each can be evaluated both positively and negatively, the analysis addresses eighteen distinct

variables per review (nine positive and nine negative attributes). The distinction between positive and negative reviews allowed us to implement a workflow where SLDA used according to the positive or negative document. The probabilities of documents over topics (θ matrix) transformed into binary representation in accordance with the suggestions of Kim et al. (2023).

To investigate the asymmetric effects of these attributes on overall customer satisfaction, we used a univariate Generalized Linear Model for PRCA, as proposed by Mikulic and Prebežac (2008). This approach integrates with the three-factor theory of customer satisfaction developed by Matzler and Sauerwein (2002), which allows us to examine how different service attributes asymmetrically influence traveller satisfaction. Our baseline model specification is the following:

$$TS_i = a + \sum_k b_k \cdot X_{ki} + \sum_l \gamma_l \cdot Y_{li} + e_i$$

where i is a review index, b_k represents the coefficient related to the k^{th} positive attribute for review i and γ_l represents the coefficient associated with the l^{th} negative attribute for the individual review i . Attributes (X_k and Y_l) include Location, Personnel, Food, Cleanliness, Comfort, Facilities, Room, Price and Service processes reflected in online reviews.

We analysed approximately 260,000 reviews from the Booking.com platform, covering six Greek destinations (e.g., Athens, Corfu) over a three-year period.

The next table describes the empirical results of PRCA including binary attribute variables as the independent variables and overall customer satisfaction rating as the dependent variable. The proposed model explains 23% of the customer satisfaction variance. The estimated coefficients show that all positive attributes caused positive effects, whereas all negative attributes brought about negative effects, as previously expected. Using the five categories suggested by Mikulić and Prebežac (2008), the impact index (IAI) depicts in the next table.

	Athens	Chalkidiki	Corfu	Crete	Kalamata	Rhodes
Location	DS	DS	F	DS	F	F
Personnel	H	DL	S	S	DL	S
Food	S	H	H	S	DL	S
Cleanliness	H	F	F	F	DS	H
Comfort	S	S	S	DL	DL	S
Facilities	H	H	S	H	DL	H
Room	DL	DL	DL	DL	DL	DL
Price	DL	DL	H	H	S	F
Processes	S	F	S	DL	DL	DL

Table 2: Impact of service attributes across destinations (F-frustrator, DS-dissatisfier, H-hybrid, S-satisfier, DL-delighter)

Different Greek destinations produce varying results. However, factors such as Location and Cleanliness are fundamental across all destinations. These factors are part of travellers' basic service expectations-while their absence may cause dissatisfaction, their improvement does not necessarily enhance satisfaction. The analysis

highlights key service attributes affecting traveller satisfaction across Greek destinations. Location acts as a dissatisfier or frustrator, meaning poor performance leads to dissatisfaction, but improvements may not significantly boost satisfaction. Cleanliness and room quality are strong delighters, enhancing satisfaction when well-executed. Personnel and comfort vary in impact, with notable positive effects in Chalkidiki and Kalamata. Price perception differs, with Rhodes showing high sensitivity. To optimize service quality, efforts should focus on minimizing dissatisfiers like poor processes in Chalkidiki while enhancing delighters such as cleanliness and customer service.

The impact of Service Attributes on Traveller Satisfaction in hotels varies across locations, influenced by differing preferences and expectations. Some attributes have symmetric effects, while others influence satisfaction asymmetrically. By analysing online reviews, hotels can refine their service offerings to better meet guest needs, reducing dissatisfaction and enhancing positive experiences. This targeted approach can lead to improved performance indicators, such as higher ratings and increased profitability.

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References

- Albayrak, T., and Caber, M. (2015). "Prioritisation of the hotel attributes according to their influence on satisfaction: A comparison of two techniques," *Tourism Management*, 46, 43-50.
- Bi, J. W., Liu, Y., Fan, Z. P., and Zhang, J. (2020). "Exploring asymmetric effects of attribute performance on customer satisfaction in the hotel industry," *Tourism Management*, 77, 104006.
- Brandt, R. D. (1988). "How service marketers can identify value-enhancing service elements," *Journal of Services Marketing* 2 (3), 35-41.
- Bui, H. T. and Robinson, P. (2024). "The asymmetric effect of all-inclusive holiday service quality attributes on tourist satisfaction," *Journal of Vacation Marketing*, 13567667241229447.
- Guo, Y., Barnes, S. J., and Jia, Q. (2017). "Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation," *Tourism management*, 59, 467-483.
- Kim, J. M., Liu, J., and Park, K. K. C. (2023). "The dynamics in asymmetric effects of multi-attributes on customer satisfaction: evidence from COVID-19," *International Journal of Contemporary Hospitality Management*, 35(10), 3497-3517.
- Lee, J. S. and Choi, M. (2020). "Examining the asymmetric effect of multi-shopping tourism attributes on overall shopping destination satisfaction," *Journal of Travel Research* 59 (2), 295-314.
- Martilla, J. A. and James, J. C. (1977). "Importance-performance analysis," *Journal of Marketing* 41 (1), 77-79.
- Matzler, K. and Sauerwein, E. (2002). "The factor structure of customer satisfaction: An empirical test of the importance grid and the penalty-reward-contrast analysis," *International Journal of service industry management* 13 (4), 314-332.

Matzler, K., Sauerwein, E., and Heischmidt, K. (2003). "Importance-performance analysis revisited: The role of the factor structure of customer satisfaction," *The Service Industries Journal* 23 (2), 112-129.

Mikulić, J. and Prebežac, D. (2008). "Prioritizing improvement of service attributes using impact range-performance analysis and impact-asymmetry analysis," *Managing Service Quality: An International Journal* 18 (6), 559-576.

Parasuraman, A., Zeithaml, V. A., and Berry, L. L. (1988). "SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality," *Journal of Retailing* 64 (1), 12-40.

Watanabe, K. and Baturu, A. (2024). "Seeded Sequential LDA: A Semi-Supervised Algorithm for Topic-Specific Analysis of Sentences," *Social Science Computer Review* 42 (1), 224-248.

AGE-RELATED DIFFERENCES IN ATTITUDES TOWARDS, AND USAGE OF, CHINESE AI AND SOCIAL MEDIA APPLICATIONS AMONG U.S. CITIZENS

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Keywords: AI race, geopolitical competition, united states, china, age, demographics, apps.

As digital platforms increasingly transcend national boundaries, and the technological competition between the U.S. and China, particularly in the development of artificial intelligence (AI) is increasingly at the center of geopolitics, understanding demographic variations in technology adoption and trust becomes crucial for both market participants and policymakers. For instance, for people old enough to have experienced the Cold War, the way that younger generations have flocked to using Chinese apps such as TikTok is incomprehensible. The seeming disregard by young people for data privacy, security, and the flow of data to China – things that are of acute concern to older generations – shows a vast generational divide over the nature of the geopolitical competition between the two nations in the development of advanced digital technology. This study specifically investigates how different age cohorts in the United States navigate the complex interplay between technological and social utility, data privacy concerns, and geopolitical considerations when engaging with Chinese-developed applications.

Launched in the U.S. in October 2018, by October 2024, 50.6% of the U.S. population had a TikTok account (Statista, 2024:1), with over 120 million monthly active users (Statista, 2024:2). Amongst the U.S. population, as of May 2023, 69.7% of people aged 12-17, and 76.2% of 18-24 year-olds were active TikTok users, compared to just 13.9% of 55-64 year-olds and 6.7% of those aged 65+. (eMarketer, 2023). In contrast, for TikTok's most comparable U.S. competitor, Instagram, while the penetration for younger users is similar, with 78% of people aged 18-29 using Instagram, 35% of people aged 50-64 and 15% of people over 65 use Instagram, roughly double the adoption rate of TikTok in these older age demographics (Backlinko, 2025). Facebook is even more widely used by older adults, with 71% of American adults over 50 using the social media platform (AARP, 2023). More recently, the launch of DeepSeek, an AI chatbot out of China, rivaling the performance of Chat GPT and other US AI models, despite their limited access to advanced chips from Nvidia, caused a shockwave through the markets and the AI developer community, with prominent Silicon Valley venture capitalist Marc Andreessen calling it "AI's Sputnik moment" (Fortune, 2025). Yet, despite this concern of the appearance of an advanced Chinese AI app as a threat to the US lead in the AI race, within a week of its launch it was the most downloaded app in the U.S. on both the iPhone and Android platforms, driven by the adoption by young people. If indeed the outcome of the race between the U.S. and China in the development of AI is as critically important in the balance of power between the two nations, as many politicians and pundits assert, then the mass adoption of Chinese AI and related apps by U.S.

younger demographics is of critical concern and could help tilt the momentum of this race in favor of China. Accordingly, research into the attitudes and behaviors of different age-demographics can shed light into the likely dynamics of this race going forward.

In exploring the particular issue of the adoption of Chinese versus U.S. apps by different age demographics, we need to be able to disentangle general differences in technology adoption by different age cohorts. The Technology Acceptance Model (TAM) (Davis, 1986) has been widely tested in empirical studies and demonstrates consistent and stable findings of the negative correlation between age and technology adoption. Accordingly, *ceteris paribus*, we should expect higher adoption rates of new apps amongst younger age cohorts than amongst older age cohorts. However, this negative impact of age on intention to use new technology has been shown to be fully mediated by perceived ease of use (Hauk, Huffmeier, & Krumm, 2018). While no current data is available for the use of AI apps, the fact that 71% of American adults over the age of 50 use Facebook implies that for social media at least, age is not a large barrier for the adoption of social media *per se*. However, disentangling the effects of age with other security and privacy concerns over the origin of different apps remains to be studied.

This paper proposes to take a first step in disentangling age from security, privacy, and geopolitical concerns as it relates to the adoption of Chinese social media and AI apps. Research will be conducted using quantitative survey data to develop a nuanced understanding of age-based variations in adoption patterns of Chinese apps and underlying decision-making processes. We will be undergoing a nationally representative survey (N=2,400) stratified across six age cohorts corresponding to generational cohorts: Gen Z (aged 13-28), Millennials (aged 29-44), Generation X (aged 45-60) and Baby Boomers II (aged 61-70) Baby Boomers I (aged 71-79) and the Silent Generation (aged 80+). The survey will measure variables including: current usage patterns of Chinese applications, perceived benefits and risks, privacy concerns, attitudes towards China and Chinese apps, trust factors, and demographic variables. Preliminary results will be available by the time of the LMDE conference in June, 2025.

The results from this study can potentially inform policymakers who are concerned with the geopolitical ramifications of U.S. citizens utilizing Chinese apps – a highly visible current issue. Chinese data protection laws mandate that tech companies can be compelled to share user data with government authorities, raising significant national security and privacy concerns for Americans. Indeed, DeepSeek's terms of service makes the possibility of this data transfer explicit. The Chinese Cybersecurity Law (2016) and National Intelligence Law (2017) effectively require Chinese companies to cooperate with state intelligence gathering, potentially exposing US users' personal information to government surveillance. This creates a complex legal and ethical landscape where data transferred through Chinese AI platforms could be subject to Chinese government access, potentially compromising individual privacy and potentially exposing sensitive personal or professional information to state-level intelligence operations. The risk is particularly acute given the ongoing technological and strategic tensions between the U.S. and China, where data has become a critical geopolitical asset. Ultimately, the AI race represents more than

a technological contest; it could lead to a profound restructuring of global power dynamics, where technological capability increasingly determines geopolitical influence and strategic positioning on the world stage.

References

Davis, F.D., (1986). A technology acceptance model for empirically testing new end-user information systems: theory and results. Doctoral dissertation, Sloan School of Management, MIT.

AARP (2023). 2023 Tech Trends and Adults 50+ https://www.aarp.org/content/dam/aarp/research/surveys_statistics/technology/2023/2023-tech-trends.doi.10.26419-2Fres.00584.001.pdf.

Backlinko (2025). Instagram Statistics: Key Demographic and User Numbers. January 30, 2025. <https://backlinko.com/instagram-users>.

eMarketer. (September 18, 2023). TikTok reach in the United States as of May 2023, by age group [Graph]. In Statista. Retrieved January 31, 2025, from <https://www.statista.com/statistics/1095196/tiktok-us-age-gender-reach/>.

Fortune (2025). Marc Andreessen warns Chinese ChatGPT rival DeepSeek is “AI’s Sputnik moment.” By Christian Hetzner, January 27, 2025. <https://fortune.com/2025/01/27/marc-andreessen-deepseek-sputnik-ai-markets/>.

Hauk, N., Hüffmeier, J., & Krumm, S. (2018). Ready to be a silver surfer? A meta-analysis on the relationship between chronological age and technology acceptance. *Computers in Human Behavior*, 84, 304-319.

Statista (2024:1). We Are Social, & DataReportal, & Meltwater. (October 23, 2024). TikTok penetration in selected countries and territories as of October 2024 [Graph]. In Statista. Retrieved January 31, 2025, from <https://www.statista.com/statistics/1299829/tiktok-penetration-worldwide-by-country/>.

Statista (2024:2) DataReportal, & We Are Social, & Meltwater. (July 31, 2024). Countries with the largest TikTok audience as of July 2024 (in millions) [Graph]. In Statista. Retrieved January 31, 2025, from <https://www.statista.com/statistics/1299807/number-of-monthly-unique-tiktok-users/>.

THE DIGITAL MIRROR: SOCIAL MEDIA INFLUENCERS, AI, AND THE RECONSTRUCTION OF IDEALIZED FEMININITY

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Keywords: Social media influencers, AI, beauty standards, data analytics, conspicuous consumption, co-creation, self-esteem, brand loyalty.

The evolution of social media has redefined beauty standards, shifting influence from traditional advertising to digital culture. Historically, cosmetic marketing leveraged scientific discourse to establish beauty ideals, whereas today, social media influencers mediate brand-consumer interactions, actively shaping aesthetic norms. This study investigates the role of social media influencers in reconstructing idealized femininity, emphasizing the interplay between influencer marketing, consumer self-perception, and conspicuous consumption. By drawing parallels with historical beauty advertising, the study critically examines how digital platforms amplify beauty norms. Additionally, it explores the transformative impact of artificial intelligence (AI) and data analytics in optimizing influencer marketing strategies, targeting consumer behavior, and refining beauty trend dissemination. AI not only reinforces beauty standards but also plays a pivotal role in influencing consumer decision-making, engagement, and branding strategies within influencer marketing. AI-driven recommendation algorithms, virtual influencers, and predictive analytics influence both content visibility and user perception, shaping decision-making processes and contributing to the digital economy of influencers by determining engagement rates, brand partnerships, and monetization strategies.

This study is grounded in three key theoretical frameworks. First, Gender Performativity (Butler, 1990) posits that femininity is not an inherent characteristic but rather a performance constructed through repeated cultural and social practices. Social media influencers play a crucial role in reinforcing these performances by curating content that promotes specific beauty standards, thereby shaping consumer perceptions of femininity.

Second, Conspicuous Consumption (Veblen, 1899) highlights how individuals purchase beauty products not merely for their functional benefits but as a means of signaling social status. Influencers, by showcasing aspirational lifestyles and luxury beauty items, fuel this phenomenon, encouraging followers to consume products that align with these elite aesthetic ideals. AI-driven data analytics further amplify this dynamic by identifying high-value consumers, tailoring personalized marketing messages, and optimizing influencer partnerships to maximize engagement and sales.

Lastly, Value Co-Creation (Prahalad & Ramaswamy, 2004) underscores the participatory nature of modern beauty culture, where social media users are no longer passive recipients of marketing messages but active contributors to the construction of beauty norms. Through interactions such as likes, comments, and engagement with influencers, consumers help shape emerging trends, blurring the traditional boundaries between producers and consumers in the digital beauty industry. AI enhances this process by analyzing user engagement patterns, allowing brands to

anticipate emerging beauty trends and dynamically adjust influencer content strategies.

Anchored in such theoretical perspectives, this research highlights the performative nature of femininity and the aspirational aspects of luxury beauty products. The study focuses on two key research questions: (1) How do social media influencers shape beauty norm performativity? (2) How do AI and data analytics refine influencer marketing strategies and beauty trend propagation?

A mixed-methods approach was employed, combining qualitative and quantitative techniques. The sample selection followed purposive sampling criteria, ensuring representation across different levels of influencer exposure, age groups, and socioeconomic backgrounds. Focus groups and semi-structured interviews with influencers provided insights into the perception and reinforcement of beauty norms, while a netnographic study analyzed social media interactions. A survey of 400 Moroccan women aged 18 to 45 was conducted to assess the impact of influencer exposure on self-esteem and brand loyalty, complemented by structural equation modeling to evaluate interrelationships between key variables. Participants were selected based on their active engagement with beauty-related influencer content and their purchase behavior in response to influencer marketing campaigns.

AI applications in data analysis played a crucial role in uncovering patterns in influencer marketing effectiveness. Sentiment analysis was used to assess consumer reactions to beauty-related posts, tracking emotional responses and engagement levels. Machine learning-based clustering techniques identified consumer segments based on interaction patterns, enabling a more precise understanding of how different audiences respond to idealized femininity portrayals. Additionally, AI-driven predictive modeling was employed to analyze purchasing trends, estimating the likelihood of consumer conversion based on exposure to influencer-endorsed content. These analytical techniques provided a data-driven foundation for evaluating the impact of AI-optimized influencer strategies on consumer behavior. Furthermore, AI-driven automation in digital marketing has streamlined decision-making processes for brands, reducing costs associated with market research, campaign management, and audience segmentation, thereby enhancing overall economic efficiency. AI also enables dynamic pricing models and real-time content adaptation, ensuring that brands maximize their ROI while influencers optimize audience engagement through algorithmically curated content.

Findings confirm that social media influencers, reinforced by AI and data analytics, significantly shape contemporary beauty norms. AI-driven reinforcement of beauty standards pressures individuals to conform, with 80% of participants reporting an increased desire to align with influencer-promoted ideals. Conspicuous consumption is heightened by AI-powered personalization, with 70% of respondents purchasing luxury beauty products influenced by aspirational content. Psychological effects on self-esteem are evident, particularly among younger women, with 65% reporting a decline in self-perception following repeated exposure to idealized images. Additionally, consumer engagement and AI-driven predictive analytics enhance brand loyalty, as 58% of participants demonstrate a strong preference for influencer-endorsed products. AI's ability to personalize advertising, analyze consumer sentiment, and predict purchasing behavior reinforces its centrality in brand-

ing strategies, making it an indispensable tool for influencer marketing. Economically, AI's role in digital marketing facilitates cost-effective consumer targeting, increasing return on investment (ROI) for brands by ensuring higher conversion rates and optimizing resource allocation. Platforms like Instagram and TikTok integrate AI to refine ad placements, curate personalized feeds, and drive influencer-brand collaborations, directly shaping market dynamics.

This study contributes to academic literature by illustrating AI's role in accelerating beauty norm construction via algorithmic amplification and personalized content dissemination. Influencer marketing is no longer solely organic but increasingly optimized through AI-driven analytics, reshaping consumer perception, self-esteem, and purchasing behavior. However, ethical concerns arise regarding AI's role in amplifying unrealistic beauty standards and encouraging conspicuous consumption. Regulation of AI in digital marketing could serve as a mitigating factor, ensuring that AI-driven content recommendations do not disproportionately promote unattainable beauty ideals. Ethical AI frameworks should be established to balance commercial interests with consumer well-being, incorporating guidelines on transparency, fairness, and content moderation. For brands and marketers, the findings emphasize the need for responsible AI use to prevent the reinforcement of exclusive and harmful beauty standards. For influencers, responsible content curation is crucial. Reducing reliance on filters and excessive digital modification while promoting authentic representation fosters healthier beauty standards. AI tools should be leveraged ethically to personalize content without exacerbating harmful beauty stereotypes.

Further research is needed to compare AI-driven influencer marketing across cultural contexts, investigate the impact of AI-generated virtual influencers on consumer perception, and develop ethical AI guidelines for influencer marketing, ensuring fair algorithmic content promotion. In conclusion, social media influencers, empowered by AI and data analytics, play a decisive role in reconstructing idealized femininity. AI-driven marketing strategies optimize engagement, personalize advertising, and reinforce aspirational beauty ideals. While these technological advancements create opportunities for brands, they also raise ethical concerns regarding consumer well-being, self-esteem, and beauty diversity. A responsible and transparent approach to AI in influencer marketing is essential to fostering a more inclusive and ethical digital beauty landscape.

Session C6

LAW, IP AND

ETHICAL IMPLICATIONS OF AI

Chair: Stina Teilman-Lock, Copenhagen Business School, Denmark

INTELLECTUAL PROPERTY RIGHTS AND AI-GENERATED WORKS: LEGAL AND ECONOMIC CHALLENGES

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Keywords: Artificial intelligence, governance, intellectual property.

The rapid advancement of Artificial Intelligence (AI), particularly generative AI models like ChatGPT, presents unprecedented challenges to traditional Intellectual Property Rights (IPR) frameworks. These models, capable of creating human-like text, music, art, and even software code, blur the lines of authorship and ownership, forcing a re-evaluation of existing legal and economic paradigms. This paper delves into the complex interplay between AI and IPR, examining the legal and economic implications of extending (or not extending) IPR protection to AI-generated works, and proposing policy recommendations to navigate this evolving landscape.

The core issue lies in the traditional focus of IPR on human creativity. Copyright law, for instance, typically protects original works of authorship fixed in a tangible medium, requiring human creation as a fundamental criterion. This poses a significant challenge for AI-generated outputs, where the "author" is a machine. Patent law, with its emphasis on human invention, faces similar hurdles. While trademarks and trade secrets offer some protection for branding and confidential information related to AI development, they do not address the core issue of ownership of the creative outputs themselves.

Several high-profile cases illustrate the legal ambiguities surrounding AI-generated works. The Thaler case, involving a patent application for an AI-generated invention, highlighted the resistance to recognizing AI as an inventor. Similarly, the revocation of copyright for a comic book partly generated by Midjourney underscores the uncertainty surrounding copyright protection for AI-generated content. OpenAI's stance of not claiming IPR over ChatGPT-generated content further complicates the issue. The US Copyright Office's denial of registration for works "produced by a machine...without any creative input or intervention from a human author" reinforces the human-centric nature of current copyright law. However, the required level of human involvement remains ambiguous, as evidenced by the J. Allen case, where extensive prompt engineering and post-generation editing were deemed insufficient for copyright protection.

Jurisdictions are grappling with these challenges in different ways. The UK, along with several other countries, offers limited protection for "computer-generated works," designating the person who made the "necessary arrangements" as the author, albeit with a shorter protection period and no moral rights. This approach avoids the thorny issue of AI authorship but may not adequately address the incentives for innovation. China's judiciary has taken a more active role, establishing criteria for copyright protection of AI-generated works based on the extent of human

involvement. Cases like *Feilin v. Baidu* and *Shenzhen Tencent v. Shanghai Yingxun* demonstrate the emphasis on human input for copyright eligibility. However, the legal status of fully autonomous AI-generated works remains unclear.

Beyond the ownership of AI-generated outputs, the issue of training data raises further legal and ethical questions. The use of copyrighted material in AI training, even if transformed, blurs the lines of fair use. The Getty Images lawsuit against Stability AI, alleging copyright infringement through the use of copyrighted images in training data, highlights the complexities of this issue. The "fair use" defense, which balances creator rights with public access, is being tested in the context of AI training. The question is whether training AI models on copyrighted works, especially when the resulting AI can create competing works, constitutes fair use. Ongoing lawsuits, like the one filed by the New York Times, challenge this notion, arguing that such training creates direct competitors and undermines existing business models.

The use of pirated material in AI training adds another layer of complexity. The "Books3" dataset, containing a significant number of pirated books, exemplifies this problem. While some argue that the market will eventually find a balance, similar to the music industry's response to digital piracy, the need for regulations and transparency is evident. Some companies, like Adobe, are emphasizing ethical data sourcing and creator compensation. The option for creators to "opt out" of having their data used for AI training is also gaining traction.

The economic implications of extending IPR to AI-generated works are far-reaching. While it could incentivize investment in AI research and development, it also raises concerns about the potential for monopolies and stifled competition. Overly broad IPR protection could hinder innovation by creating a "permission culture." The impact on creative industries is also a concern. AI-generated content could disrupt existing business models and devalue human-created works. However, AI could also create new market opportunities and empower human creators with new tools. The potential displacement of human creators is a significant concern, particularly for entry-level and freelance workers. While AI could automate tasks and facilitate collaboration, it also risks fragmenting full-time positions into piece-meal gig work.

Ethical considerations and societal impacts must also be addressed. Overly strict IP protection could hinder access to AI technologies, particularly in developing economies. The intrinsic value of human creativity and the risk of homogenizing artistic styles are also important concerns. Algorithms and data biases could reinforce existing stereotypes and limit cultural diversity.

To navigate these challenges, several policy recommendations are proposed. First, copyright authorship and ownership of AI-generated works must be clarified. A "human authorship threshold" could be defined to distinguish between AI-assisted and fully autonomous AI-generated works. The "work made for hire" doctrine offers a potential model for assigning ownership, although it may not accurately reflect the creative process. Second, fair use exceptions should be modernized to accommodate the use of copyrighted materials in AI training, research, and development. Alternative forms of IP protection, such as *sui generis* rights for training datasets, could also be explored. A blockchain-based system for distributing digital content

could offer greater control and transparency for creators. Establishing a registry for AI models could further enhance transparency and accountability. Standardized licensing practices for AI-generated outputs are also needed. Finally, international cooperation and harmonization of IP laws related to AI are crucial for fostering innovation and preventing regulatory fragmentation. Increased transparency in AI model training, as pursued by initiatives like the EU's AI Act and the US Executive Order on AI, is a crucial first step. These combined measures aim to balance the interests of all stakeholders and ensure a sustainable and equitable future for the creative and knowledge economies in the age of AI.

AI, ADVANCED TECHNOLOGIES, AND THE NEED TO REVISE COPYRIGHT LAW

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Keywords: Copyright, copyright relaxation and reuse of protected materials, copyright and AI, copyright and technological infringement.

We address four research questions, motivated by the increasing use of technology in the production of innovative works in music, literature, journalism, and the arts. How should copyright law be modified to assure that creative reuse of existing works is protected, to ensure that society has the greatest total access to creativity, both original works and works derived in part from those original works?

1. How should existing protections be reduced for the optimal benefit to society? How should copyright law be modified to ensure that the existing owners of copyright on original works can be adequately rewarded when their works are creatively reused, either by human artists or AI agents?
2. How should existing protections be enhanced, and what new protections for existing works should be introduced, to ensure the optimal benefit to society?
3. When AI agents create novel works what copyright protections should be extended to works and how should protections be divided among the creator of the agent and the artist who used the AI agent to produce the work?
4. When AI agents are trained on a massive body of existing works and then create novel works how should the owners of copyright on inputs to the AI agent be protected?

Copyright law is designed to provide society with the greatest access to innovative and creative content, not merely to protect artists and their works. If creativity is difficult, time-consuming, or expensive, then protecting creators and their works is essential to ensuring adequate supply of innovation. However, copyright protection must not become excessively rigid, in order to ensure adequate access to innovation. Copyright law has changed over the centuries, as the balance shifts between the need to ensure adequate supply of innovation and adequate access to innovation. If technology makes it easier to create innovative content, then any balance between supply and access that existed previously must now be obsolete. Likewise, if technology makes it easier to create innovative content and valuable work through reuse of existing protected works, then any balance between supply and access that existed previously must now be obsolete.

Early copyright law, the 1710 Statute of Anne in the United Kingdom and the French Act of 19-24 July 1793, provided a simple protection against direct copying. Copyright law protected authors and publishers' investments in literary and artistic works. A rationale for copyright was that it offered a protection against copying that would destroy the value of originals. This copying was seen socially harmful to the

public, in addition to being harmful to the author. Since the beginning of copyright there have always been attempts to justify the exclusive right to copying and to balance the value to the author and to society.

Technologically-enabled creative use of protected materials is increasing, and the reuse is both easier and more valuable, motivating our first research question. Technologies for creative modification and enhancement have become so powerful and easy that ultimately most forms of reuse will be feasible for almost anyone to implement, not merely the original creator. Therefore, we focus our analysis solely on the copyright implications of reuse by parties other than the original creator. We consider (1) recreation of the original work, but in higher quality, which we can call reperformance; and (2) creation of new works that appear to be due to the original creator, or homage works.

As an example of reperformance, consider the many recent recordings of Gershwin and Scott Joplin playing their own piano works. There are numerous technologies for achieving this, some based on old low-quality analog recordings and others on “digital” piano rolls. Hearing Gershwin play *Rhapsody in Blue* along with a modern orchestra must have been artistically as well as technologically memorable, and surely had considerable social value. In the case of dead artists whose works are out of copyright this poses no problems, but where copyright persists there are legal and economic issues that need to be resolved. We believe that such reuse is unambiguously valuable and should be encouraged, but that compensation to the original creator is essential and rules for its calculation need to be developed.

When homage works are authorized they clearly pose no problems. *Buried Secrets* is a novel by Christopher Farnsworth, in the style of Robert B. Parker and based on Parker’s character Jesse Stone. Many of Tom Clancy’s later novels were written by other authors, who were acknowledged and compensated. However, when works are written in the style of another author, or musical works are performed with the waveform of another musician, or readings are performed with the voice of a famous actor, without authorization, this becomes more problematic. Harrison Ford has said that you don’t need AI “to steal his soul”; it can “now be done for nickels and dimes.” Actors have been speaking out about using technology to steal their voices, and the Screen Actors Guild-American Federation of Television and Radio Artists called a strike in defense of actors’ right to control the reuse of their voices. Analysis is complex. When reuse is harmful, such as a deep fake that tried to portray an artist as a Nazi sympathizer or a child abuser, it should unambiguously be prohibited. When reuse creates new works with artistic value, and does not harm the reputation of the original artist, it should be permitted. But how should revenues be allocated? And, in the case of living artists who are still performing, how should revenues be handled in cases where the original artist might have eventually chosen to perform the new work? Again, value-creating reuse should be permitted, a form of mandatory licensing more commonly associated with critical vaccines and defense procurement, but formula for revenue division must be developed and will be complex.

Historically, creative works were produced by people, working individually, in groups, or for the organizations that employed them, and copyrights were granted to individuals and retained by those individuals or by their employers. Increasingly,

innovative and original works will be created by AI agents, motivating our third question. How should the benefits of copyright be allocated among the individual who was the “final” creator of the work and the AI agent involved? If the law does not acknowledge the AI agent as a copyright holder, how should the benefits of copyright be allocated among the individual responsible for the work and the copyright holder or copyright holders of the AI agent itself? Policy and case law for legal liability for harm caused by AI agents may provide meaningful insights, since there is more experience here than with copyright for creative works developed using AI. Recent experience is inconclusive, because most cases have been settled out of court, but this experience with autonomous vehicles suggests that liability will be divided among the driver of the vehicle or vehicles involved and the creators of the AI agent. We are addressing division of benefits rather than assessment of liability.

In some sense all AI works are derived from previous work. Chatbots and predictive / generative AI are always based on or trained on databases of hundreds of thousands or even millions of documents, and perhaps hundreds of millions of words of text. Machine learning systems used in public health, medicine, or other sciences are always based on hundreds of thousands, or even hundreds of millions of individual data points. No single individual work, document, or data point is likely to have a dramatic impact on the final work created by the AI agent. Moreover, since most AI agents based on machine learning cannot provide an adequate explanation for their results, the contribution of individual works, documents, or data points usually cannot be assessed from the final result. Alternatively, their access by and use in training of AI agents may be prohibited. This motivates question 4 above.

It is simple to add the words “Please note that no part of this book may be used or reproduced in any manner for the purpose of training artificial intelligence technologies or systems,” but it is difficult to detect, confirm, or limit such use in practice. Removing the use of any single work out of hundreds of thousands is unlikely to affect the final product of the AI agent; how then can the use of that work be detected? Nash Bargaining would suggest that any single use adds no measurable value; how then can appropriate compensation be calculated?

In conclusion, we note that this remains a work in progress. For some of our questions we have documented numerous examples and analyzed litigation history, and for some special cases we have completed mathematical modeling of the sharing of profits. The work continues.

SURVIVING GENERATIVE AI: TEMPORAL TRAJECTORY OF RESILIENCE IN STACK OVERFLOW AND GITHUB

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Keywords: Temporal trajectory, resilience, crowd-driven, open-knowledge, generative AI.

Platforms such as Stack Overflow and GitHub serve as the lifeblood for global knowledge exchange for software development, yet they face profound challenges from emerging technologies like Generative AI (GAI) that accelerate knowledge creation (Chen et al., 2024) and effectively mimics humans – creating challenges ensuing human-governed, open-knowledge IS systems. These crowd-driven environments operate with a distinctive blend of openness and decentralised user governance, making them especially vulnerable when their established governance structures are disrupted. In open-knowledge platforms, the unpredictable nature of the crowd, and its importance in setting the trajectory as disruptions occur, complicates the organisation’s capacity to absorb shocks, adapt, and transform in response (Zamani et al., 2022). Understanding the temporal dynamics of these responses is crucial, as resilience is not a static state, but an evolving process shaped by how crowds engage with change over time (Hernes et al., 2025).

Through the cases of Stack Overflow and GitHub, we investigate the crowd’s temporal trajectory for resilience, and how this can lead to markedly different outcomes. Crowds in these platforms are the governing body, influencing key decisions, setting regulations, mobilising around common interests, and in these cases core to the setting of the trajectory after disruptions occur. While the crowd in Stack Overflow has more reactive responses to policy changes in response to disruptive GAI challenges, GitHub’s community has demonstrated a more anticipatory and agile response, leveraging its iterative development practices to reconfigure its governance in real time. Management’s influence in these platforms are limited by the crowds influence, which sets the stage to investigate the capabilities of crowds – more specifically anonymous, unpredictable independents within crowds – and how their temporal perceptions influence trajectory and enforce or disrupt resilience. Using the temporal trajectory model for resilience, which allows us to set clear boundary conditions – limited to this specific temporal lens, we are able to investigate how trajectories are determined in crowd-driven systems.

The evolution of resilience research has laid the groundwork for this inquiry. Early studies in resilience—spanning ecological systems (Folke, 2006), organizational contexts (Almedom, 2013; Ortiz-de-Mandojana & Bansal, 2016) and high-velocity environments (Zaheer et al., 1999)—focused on the capacity of systems to absorb shocks and reorganize without losing core functionality. Subsequent research extended these insights (Boe-Lillegraven et al., 2023; Hillmann & Guenther, 2021), emphasizing the need for adaptive capacity in rapidly evolving contexts. More recently, scholars have drawn attention to the temporal dimensions of resilience. In

this regard, Hernes et al. (2025) introduced the Temporal Trajectory Model (TTM) for resilience—a process-based approach that reconceptualizes resilience as a dynamic interplay between past experiences, present actions, and future possibilities. They suggest that instead of viewing trajectory as linear, “over time” practices – which suggest that time is linear with clear progression (the past is set in the past, the present is now, and the future comes later), a “through time” approach is more appropriate – looking at time as non-linear with instances in time intersecting before, during or after disruptions (the past, present and future trio interacts at the point of the disruption) . In our study, we look deeper into this view with crowds driving the dynamism of temporal decisions – do they consider the past, and do they plan for the future when presented with disruptions?

We propose the following research questions (RQs): RQ1: How do crowds on Stack Overflow and GitHub enact resilience through temporal decision-making, balancing past knowledge, present actions, and future possibilities in response to disruptions? RQ2: How do crowd-governed IS systems and platform affordances shape the temporal practices that enable or hinder resilience in Stack Overflow and GitHub?

To investigate these, we adopt the TTM (Hernes et al., 2025) for resilience, since unlike traditional resilience models, this model dismantles the conventional notion of resilience as a series of discrete phases and instead posits that these phases are interwoven through time. Disruptions are identified as 1) stochastic events – unpredictable and sudden, 2) probabilistic transformations – emerging and probable, or 3) tipping points - unexpected and accelerated. These events’ nature could be changed by the actors’ foresight or vigilance – which is seen in these two case studies. Through the temporal lens that this model provides, we assess how each of the platforms’ crowd manage the disruption, and how the nature of the events, as introduced by Hernes et al. (2025) can change in each case. We also aim to identify which of these platforms’ system affordances allow the crowds to most effectively address disruptions and enforce resilience. The TTM identifies three intersecting phases, which interaction could lead to resilience.

(A) Project - here, actors engage in learning from past experiences and in envisioning possible futures. Actors may have learned from the past at the moment of the disruption, to better manage the present and the future.

(B) Reconstitute - as disruptions occur, actors may apply what was learned during the project phase and set a new trajectory with emergent, real-time adjustments.

(C) Reconfigure- refers to the ability to adjust trajectory, and align with future configurations while considering the past and the present, which will also determine how the actors respond at the disruptive event.

After the immediate disruption has been managed, the focus shifts to institutionalising new mechanisms that incorporate past lessons learned and prepare the system for future shocks. The figure below (Figure 1) shows how disruptions occur throughout time, and when there’s a tipping point, organisations have the capabilities to manage it through the interplay between past, present and future.

This study employs a case study methodology (Yin, 2003) to investigate the crowd’s approach to resilience through temporal trajectory with GAI as disruptive technology in Stack Overflow and GitHub, providing insights into a real-world, contemporary issue. The research unfolds in two phases: Phase 1 involves data col-

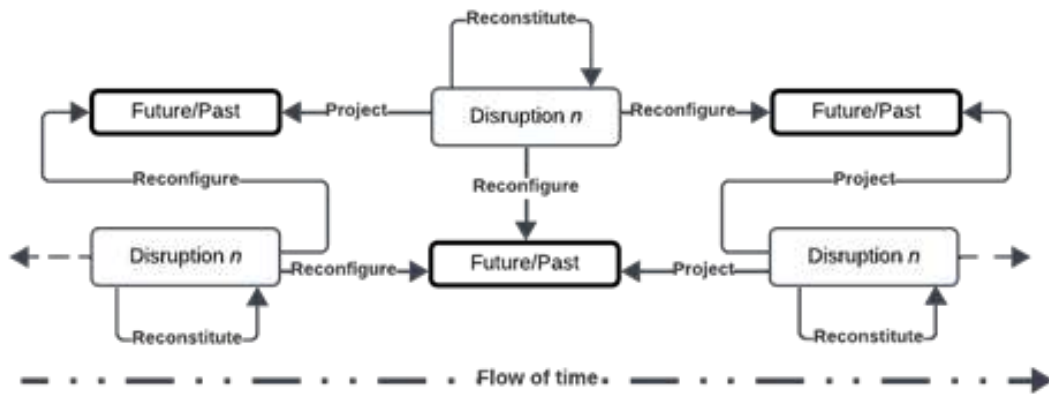


Figure 1: Adaptation of TTM of Resilience (Hernes et al., 2025)

lection – through investigating comment trends, voting patterns, moderation actions etc., case selection, and a literature review; Phase 2 uses Netnography (Kozinets, 2015) through content, trace data, and platform analysis which positions Stack Overflow and GitHub as IS cases disrupted by GAI, with crowd governance and temporal aspects.

Stack Overflow’s governance has long relied on the crowd to assist the reputation-based system—a human-centric framework built on elected moderators and community self-regulation—to ensure content quality on the platform (Jin et al., 2015). This legacy model, despite its successes, created inherent vulnerabilities, especially in light of a human-mimicking technology like GAI. For example, in 2021 a Stack Overflow user foreseen a vulnerability that GAI could exploit, saying “I will admit, it’s more sophisticated than a lot of trolling (maybe even aided by a linguistic AI to compose these questions... that would explain the buzz-words that when put together don’t really mean much)” projecting the GAI disruption, yet such concerns were dismissed by moderators and users with comments like, “If it’s getting serious enough... then we can raise issues up to the Community Team”. These early signals reflected a failure in the project phase: an independent user noticing a possible fault, informing the crowd at the moment of realisation, however this notion is then instantly rejected by the crowd, dismissing any means of preparing for the disruption. The inability to align the crowd to consider such projections are common within the platform, and sets up GAI’s disruption as a tipping point – even though these events could have been well managed in advance.

When GAI usage surged, a tipping point event existed and Stack Overflow’s immediate response was an instant and outright ban on AI-generated content—a reactive measure that epitomised its reconstituting phase. The abrupt ban, imposed without pondering alternative adaptive strategies, led to a governance crisis as moderators became overwhelmed, eventually sparking the moderator strike – where moderators mobilised against the usage of GAI, pausing their actions to govern the platform. The strike itself had an extreme temporal effect on the resilience of the platform, as no enforces allowed for the flooding of low-quality, AI generated content on the platform during this time. In the subsequent reconfiguring phase, the platform upper management attempted to address the crisis through a con-

troversial partnership with OpenAI, without engaging with the crowd. However, rather than establishing a robust, future-oriented framework, this decision was seen by the community as capitulation—effectively “selling out” the platform, with users feeling that their data was being exploited without compensation. This sequence of events which included amongst others users deleting or poisoning their contributions, underscores how an overreliance on legacy systems, a lack of proactive temporal practices, the inability of the crowd to “wait and think”, and the influence of rapid decisions/opinions driven by anonymous users in crowds, can lead to fragmented and ultimately unsustainable resilience outcomes.

GitHub’s strategic anticipation of GAI disruptions is evident in its early development of AI-assisted tools. In June 2021—over a year before ChatGPT became mainstream—GitHub launched Copilot, built on Microsoft’s innovation and early ChatGPT iterations. During its rollout, GitHub used tags like “Product Feedback”, “Shipped”, “Announcement” to engage users in its development, and kept them in the feedback loop to improve the tool in real-time. This proactive initiative, rooted in anticipatory planning and foresight, leveraged historical insights from agile development to prepare its community for the upcoming shift. By investing in beta testing and resource allocation well ahead of the disruption, GitHub established a clear projection phase that informed both its internal strategy and external communications. Cooperation is central to GitHub, with its main selling point being able to work together on coding projects in real time. Projects have a epidemiological timeline, with actions branching out to form temporal “trees” when users work together. Users can work on branches in isolation to fix bugs or experiment on new features without risk, and when approved, the branch can be pulled in, making it a part of the main project. Discussions on new features that could be implemented in GitHub, uses the same logic, allowing the crowd to safely, and inconsequentially propose trajectories – almost frozen in time. The system allows the crowd to ponder over the best approach to the upcoming disruption. They managed it more like probabilistic transformations, which allowed for planned solutions.

When GAI tools entered mainstream usage, GitHub almost didn’t feel its effects, the crowd was aligned, kept in the loop of development, and given enough time to prepare. Instead of being detrimental to their legacy system, they further developed Copilot through the integration of GAI. How the system of GitHub is set up, is to ensure a “through time” approach, it encompasses project, reconstitute and reconfigure phases, as feedback loops remain open through the duration of the epoch. Individuals can voice their opinion without the threat of abrupt decision making, there is a sense of anticipation before the disruption due to the transparency, and crowds are given tools to be proactive. These temporal practices—spanning proactive anticipation, agile recombination, and iterative reconfiguration—explain the platform’s resilience when applying the temporal lens. In contrast to more reactive models, such as Stack Overflow, GitHub’s system is designed around given the crowd “time to think”.

A key challenge in applying the Temporal Trajectory Model to these cases stems from the crowd-based nature of these platforms. Unlike traditional organisations, which operate through hierarchical structures with clear lines of authority, crowd-driven platforms depend on decentralised governance and emergent behaviours.

Phase	Stack Overflow	GitHub
Projection	No structured foresight mechanisms, rapid dismissal of early warnings, absence of phased discussions, lack of pre-emptive adaptation structures.	Feedback loops, branched discussions, phased announcements, structured timelines, beta testing cycles, anticipatory experimentation.
Reconstitution	Abrupt and immediate bans, no transition periods, reactive policy shifts, misaligned enforcement timing, delayed response to emerging issues.	Staggered implementation, iterative adaptation, pre-planned rollout phases, synchronized updates with community input.
Reconfiguration	Sudden governance changes, no structured temporal alignment between platform and crowd, rapid shifts without transition mechanisms.	Continuous refinement cycles, persistent feedback loops, long-term iteration strategies, phased governance adjustments.

Table 1: Mechanisms of time in the trajectory of resilience - Stack Overflow vs. GitHub.

Decision-making is not only distributed but also shaped by the collective agency of independent users, who may align or diverge in their responses to disruption. This creates a fundamental tension between platform governance and community adaptation: while companies like Stack Overflow and GitHub implement top-down policies, the real impact of these decisions depends on bottom-up responses from the user base. Specific temporal practices in crowd-driven contexts are therefore inherently more fluid and unpredictable than in traditional firms, which further introduces complexities of temporality that we plan to address in future research. Complexities such as how much control does the first-responder have in setting a narrative, does the speed of crowd-mobility around an issue change the trajectory, is there a snowball effect in temporality – meaning responses will exponentially become quicker as people react to disruptions – building on ”trending” posts on these platforms, does time zones affect how crowds respond to disruptions, how does prioritizing play a role in trajectory of resilience, and how does the crowd manage that, do crowds take ”breaks” to think and manage disruptions, or is the nature of crowds always reactive -as seen in the ban on GAI and Moderator Strike?

In this research we look at the trajectory itself from a high level – showing how crowds consider the three temporal epochs – being project, reconstitute and reconfigure, however the deeper temporal drive that exists in crowds are multi-layered, and requires vast research. Our future research aims to start this deep-dive into temporal practices in crowds, through mapping interactions, modelling specific components of time, testing existing theories in crowd-driven environments, seeing how control and time interacts in trajectory research, and hopefully discovering more nuances in the research of crowds, time and control in online platforms.

References

- Almedom, A. M. (2013). Resilience: Outcome, Process, Emergence, Narrative (OPEN) theory. *On the Horizon*, 21(1), 15–23.
- Boe-Lillegraven, S., Georgallis, P., & Kolk, A. (2023). Sea Change? Sense-making, Firm Reactions, and Community Resilience Following Climate Disasters. *Journal of Management Studies*.
- Chen, R., Feng, J., Godinho de Matos, M., Hsu, C., & Rao, H. R. (2024). Special Issue: AI-IA Nexus: Artificial Intelligence-Information Assurance Nexus: The Future of Information Systems Security, *MIS Quarterly*.
- Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change*, 16(3), 253–267.
- Hernes, T., Blagoev, B., Kunisch, S., & Schultz, M. (2025). From Bouncing Back to Bouncing Forward: A Temporal Trajectory Model of Organizational Resilience. *Academy of Management Review*, 50(1), 72–92.
- Hillmann, J., & Guenther, E. (2021). Organizational Resilience: A Valuable Construct for Management Research? *International Journal of Management Reviews*, 23(1), 7–44.
- Jin, Y., Yang, X., Kula, R. G., Choi, E., Inoue, K., & Iida, H. (2015). Quick Trigger on Stack Overflow: A Study of Gamification-Influenced Member Tendencies. 2015 IEEE/ACM 12th Working Conference on Mining Software Repositories, 434–437.
- Kozinets, R. V. (2015). Netnography. In *The International Encyclopedia of Digital Communication and Society* (pp. 1–8). Wiley.
- Ortiz-de-Mandojana, N., & Bansal, P. (2016). The long-term benefits of organizational resilience through sustainable business practices. *Strategic Management Journal*, 37(8), 1615–1631.
- Zaheer, S., Albert, S., & Zaheer, A. (1999). Time Scales and Organizational Theory. *The Academy of Management Review*, 24(4), 725.
- Zamani E., Griva A., Conboy K. (2022), Using Business Analytics for SME Business Model Transformation Under Pandemic Time Pressure. *Information Systems Frontiers*, 24, 1145-1166.
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POLITICAL RISK AS A REGIME SWITCHING PROCESS

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Keywords: Financial risks, global political risk, regime switching, machine learning, neural network, portfolio construction.

Introduction

Political risk can significantly affect the economic (Alesina et al., 1997) and financial (Pástor and Veronesi, 2012) stability of countries. Understanding it enables investors and policymakers to adapt their strategy to mitigate instability and identify periods of risk escalation. Traditionally, regime-switching models (Kim and Nelson, 2017) analyze time series independently. However, political risk was recently shown to have a strong systematic component leading to the identification of a global political risk P-factor (Gala et al., 2023) which is priced “everywhere” across the stock, bonds, and currency markets (Gala et al., 2024). Hence, we expect some commonality of regime-switching across countries’ political ratings.

In this paper, we analyze political risk regime switching as a group phenomenon rather than an individual one. We first use recent advances in machine learning to identify regime shifts in multiple time series (Tajeuna et al., 2023). We then develop a neural network to learn the regime features and use it to estimate the likelihood of a country remaining in its current regime or switching to a different one. Using the documented reaction of the market’s expected return to changing political risk (Gala et al., 2023; Pástor and Veronesi, 2012), we then use these probabilities to build portfolios. The last step, with comprehensive numerical tests in and out-of-sample, is still in progress; they will be reported at the Athens conference.

Regime identification

We start by identifying whether a country’s political risk rating proxy exhibits the same regime characteristics as other countries using the multivariate regime-switching model of Tajeuna et al. (2023). This model clusters countries based on their political risk ratings time series similarity. Specifically, we apply this method to the International Country Risk Guide (ICRG PRS 2005) political ratings on a sample of 42 countries from 1993 to 2019.

We use a sliding window on each country’s political rating time series and calculate a similarity metric across countries. A high similarity metric implies that two countries exhibit the same regime and share a common risk pattern in the selected time window. We use this metric to cluster countries based on the regime they exhibit. This allows us to treat a regime as a group property, capturing more complex relationships than traditional models. We optimized the sliding window (selecting 46 months) and ran our algorithm on the entire dataset to identify three unique regimes in the full sample: countries with low political risk (L), countries with high political risk (H), and countries with a decreasing political risk (D). In Figure 1, we display the centroids describing the three regimes.

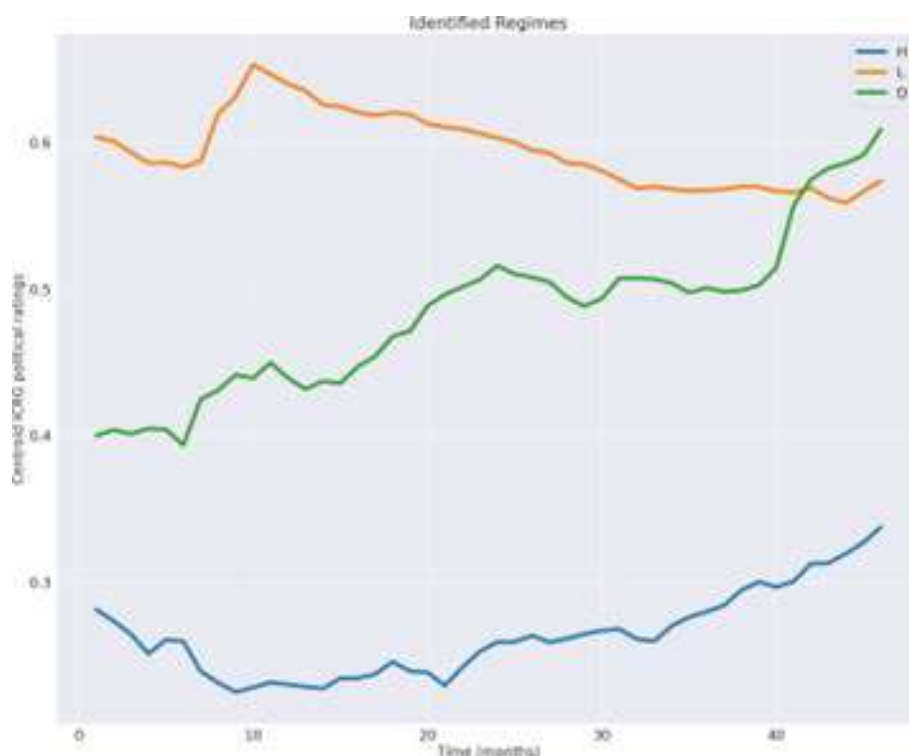


Figure 1: Common regimes of the country political ratings.

Regime feature learning

To study the features of the identified regimes, we present each group as a graph, where the edges represent the strength of the relationship between the ratings of two countries. At different points in time, we have different clusters and, hence, different graphs, and we track how these graphs and the regimes they represent change over time. We then use a Graph Autoencoder (GAE) to study the regimes and uncover the political risk relationships between countries. Each graph corresponding to a regime can be expressed as an adjacency matrix, and using the GAE, we aim to recreate this matrix while retaining as little information as possible. Our implementation learns the relationships with 95% accuracy. This implies an effective regime identification and provides a low-dimensional description of political risk relationships. We observe from Figure 2 the similarity between the original and recreated adjacency matrices.

Currently, we cannot say if the accuracy of the GAE translates to high predictive performance in forecasting regime shifts. We plan to use what the GAE learned to estimate the likelihood of a country remaining in its current regime or switching to a different one and build portfolios.

Conclusion

We use a state of the multivariate regime-switching model to identify common regimes of political risk across countries. We identify relatively stable regimes with clearly low, high, or decreasing political risk and reduce the dimensionality of the country relationships as a low-rank relationship with the common regimes. Our model relies on political risk instead of financial metrics to provide a new risk as-

assessment tool for international markets. It allows investors to take advantage of stable or unstable market periods. However, the success of the model hinges upon our ability to estimate the probabilities of transition across regimes; this is our ongoing research.

References

Alesina, A., N. Roubini, and G. D. Cohen. (1997). *Political Cycles and the Macroeconomy*, Cambridge, MA: The MIT Press.

Gala, V. D., G. Pagliardi, I. Shaliastovich, and S. A. Zenios. (2024). Political risk everywhere. Working paper, available at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4674860, BI Norwegian Business School.

Gala, V. D., G. Pagliardi, and S. A. Zenios. (2023). Global political risk and international stock returns. *Journal of Empirical Finance*, 72, 78–102.

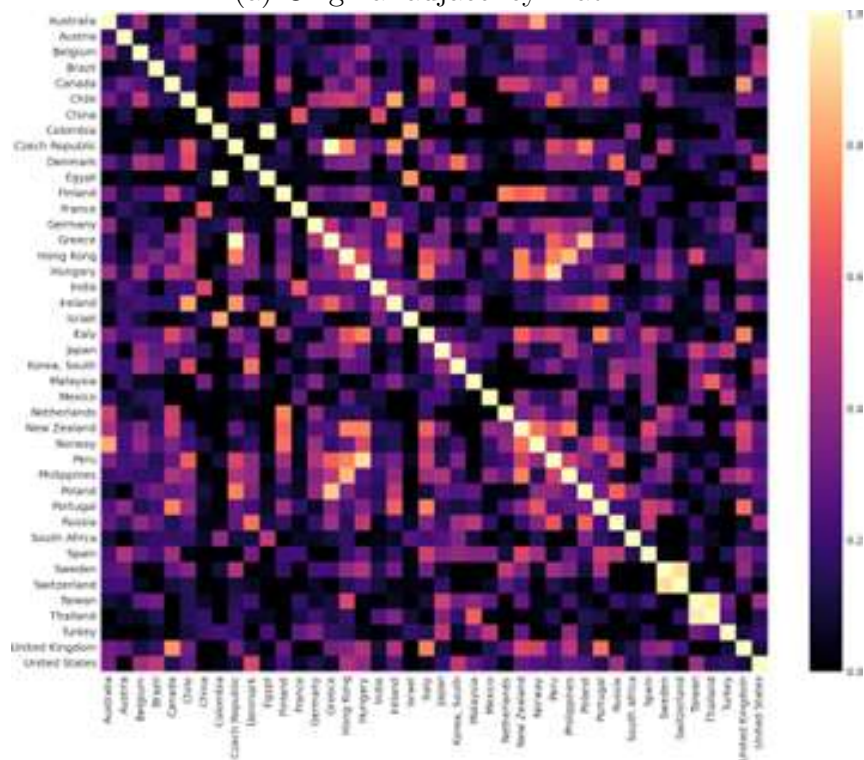
Kim, C.-J. and C. R. Nelson. (2017). *State-space models with regime switching: classical and Gibbs-sampling approaches with applications*, MIT press.

Pástor, L. and P. Veronesi. (2012). Uncertainty about government policy and stock prices. *The Journal of Finance*, 67, 1219–1264.

PRS. (2005). About ICRG: the political risk rating. Tech. rep., Available at <http://www.icrgonline.com/page.aspx?pagecrgmethods>.

Tajeuna, E. G., M. Bouguessa, and S. Wang. (2023). Modeling Regime Shifts in Multiple Time Series. *ACM Trans. Knowl. Discov. Data*, 17, 1–31.

(a) Original adjacency matrix



(b) Recreated adjacency matrix

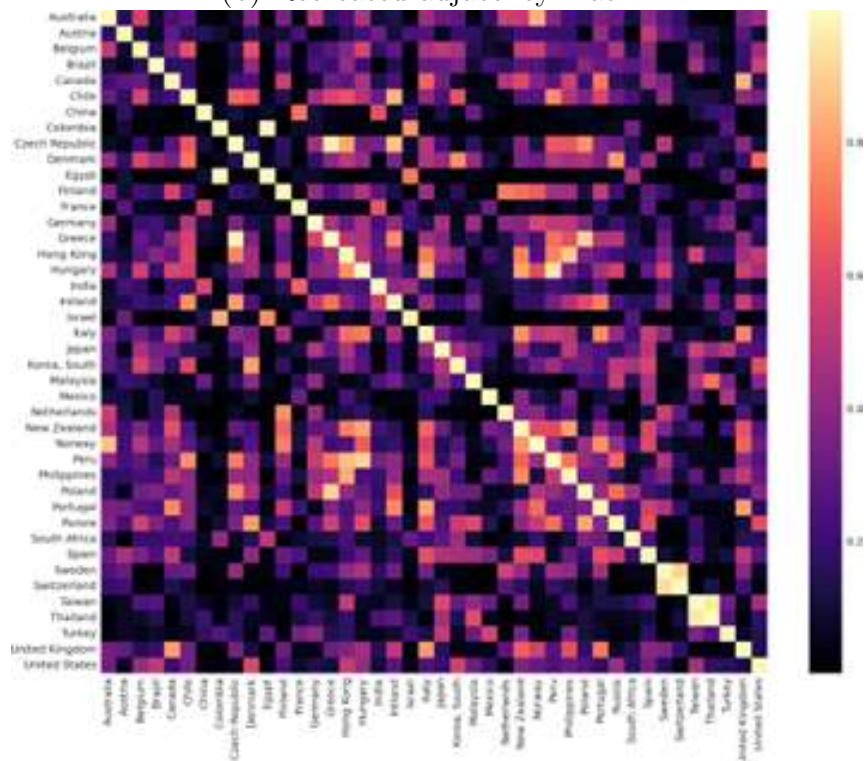


Figure 2: Comparison of the country adjacency matrices.

Session D6

**AI INNOVATIONS IN
BUSINESS EDUCATION**

**Chair: May Portuguese-Castro, PUCP - Pontificia Universidad Católica
del Peru, Peru**

CO-TEACHING WITH AI-POWERED CHATBOTS: ROLE-PLAYING SIMULATIONS AND THE FUTURE OF BUSINESS EDUCATION

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Keywords: Business education, AI-powered chatbots, role-playing simulations, educational innovation.

Abstract

The use of chatbots powered by large language models (LLMs), such as ChatGPT, is transforming business education by introducing intelligent co-teaching models that combine artificial intelligence (AI) with interactive methodologies. These tools offer real-time feedback, adaptive learning pathways, and process optimization (Chen et al., 2023). Unlike traditional AI-assisted education, where chatbots serve primarily as informational tools, AI-driven role-playing simulations introduce dynamic, interactive learning environments, encouraging students to go beyond passive engagement. These simulations serve as next-generation pedagogical tools that encourage students to actively engage in business decision-making, strategic problem-solving, and leadership development (Xu, 2024). By embedding natural language processing (NLP)-enabled simulations into business curricula, chatbots are moving beyond content retrieval to become learning facilitators that guide students through complex, real-world scenarios. Additionally, AI-driven chatbots allow for adaptive scenario-building, where student responses influence the evolution of the simulations, providing a more personalized, iterative learning process that aligns with experiential learning theories.

Furthermore, virtual AI assistants encourage students to think critically and creatively by generating realistic scenarios and fostering the development of advanced cognitive skills through adaptive feedback, thereby enhancing complex thinking in business contexts (Noever & McKee, 2022). However, to maximize their impact on business education, it is essential to develop pedagogical frameworks that balance automation with human interaction, ensuring that chatbots not only complement instruction but also promote critical thinking, ethical decision-making, and problem-solving in dynamic environments.

The growing integration of chatbots in higher education has led to key findings. Chen et al. (2023) highlight that these tools can enhance creativity and productivity by reducing the workload associated with repetitive tasks. Bohorquez-Lopez (2024) identified student-centered learning and natural language processing (NLP) as emerging trends that support educational processes in business education. Marchena-Sekli and Portuguese-Castro (2025) found that work compatibility plays a significant role in the adoption of generative AI tools in entrepreneurial settings. These findings suggest that AI has transformative potential in business education by fostering interactive methodologies and promoting a more dynamic and student-centered learning experience.

Despite the potential of chatbots and AI in business education, empirical studies on their pedagogical effectiveness remain limited, and their implementation presents

various challenges. One of the main concerns is the lack of critical thinking in AI-powered tools like ChatGPT, which can generate redundant responses and, in some cases, inaccurate information due to "artificial hallucinations" (Vecchiari, 2023). From an ethical perspective, concerns persist regarding academic integrity, as students may rely on these systems to generate complete documents without genuinely developing their analytical and critical skills (Bohorquez-Lopez, 2024). In terms of integration into teaching, it remains necessary to design strategies that facilitate the effective adoption of AI in curricula, ensuring that educators and students fully leverage its pedagogical potential while preserving the fundamental role of human learning. Finally, while generative AI can facilitate valuable content creation, expert judgment remains crucial for interpreting, evaluating, and complementing AI-generated information (Kaufmann et al., 2024; Sekli & Portuquez-Castro, 2025). Without human oversight, overreliance on AI for academic and business decision-making may compromise learning quality and knowledge generation.

To examine the role of chatbots in business education and their impact on students' competency development, this study employs a Systematic Literature Review (SLR). This methodology allows for the objective identification and analysis of previous empirical studies that have explored the use of AI-powered chatbots in educational settings. The review will focus on established databases such as Scopus and Web of Science (WOS) to address key questions: Which AI-driven pedagogical strategies are most effective for chatbot integration? How do they contribute to the development of key competencies such as strategic decision-making and complex thinking? What evaluation metrics have been used to measure chatbot-driven learning effectiveness? What are the main barriers to AI adoption in business education, and how can they be addressed? To ensure research rigor, inclusion criteria will prioritize empirical studies evaluating chatbot use in higher education, particularly to identify their applicability in business and management programs.

This study aims to contribute to the theoretical framework on the integration of AI-powered chatbots in business education by exploring their impact on the development of complex thinking, strategic decision-making, and innovation. By identifying the most effective pedagogical strategies for co-teaching with chatbots, this research proposes a conceptual framework to facilitate their implementation in business programs, ensuring a balance between automation and human interaction.

From a practical perspective, this study will serve as a reference for instructional designers, educators, and academic administrators, providing recommendations on the effective integration of AI-mediated role-playing simulations into curricula. Additionally, it highlights how AI-generated learning analytics can be leveraged for personalized student assessment, competency tracking, and real-time feedback adaptation. The findings are expected to drive new interactive teaching methodologies, strengthening the graduate profile to better equip students for the challenges of the AI-driven job market.

This study is original in its focus on AI-driven role-playing in education, an emerging application that has been underexplored in the current literature. Its added value lies in its capacity to inform and guide stakeholders, including educational institutions, businesses, and policymakers, on AI's potential to transform business education. By addressing integration challenges, biases, and pedagogical

evaluation, this research proposes innovative solutions that could shape the future of business education, fostering a more dynamic, interactive, and adaptable learning experience aligned with the demands of the modern business world.

References

Bohorquez-Lopez, V. (2024). "Evolution of the use of conversational agents in business education: Past, present, and future," *Revista de Administração Mackenzie* 25(6),1-20.

Chen, Y., Jensen, S., Albert, L.J., Gupta, S. and Lee, T. (2023). "Artificial Intelligence (AI) student assistants in the classroom: Designing Chatbots to support student success," *Information System Frontiers* 25, 161–182. <https://doi.org/10.1007/s10796-022-10291-4>.

Kaufmann, C., Bai, Ch., Borgia, B., Leeuwenburgh, C., Lin, Y., Mardini, M., McElroy, T., Swanson, C., Wimberly, K., Zapata, R., Zeidan, R. and Manini, T. (2024). "ChatGPT's Role in Gerontology Research," *The Journals of Gerontology: Series A* 79(9), 1-5. <https://doi.org/10.1093/gerona/glae184>.

Marchena Sekli, G. and Portuguese-Castro, M. (2024). "Fostering Entrepreneurial Success: Unleashing the Potential of Generative AI through Technology-to-Performance Chain. A Multi-case Study Approach," *Education and Information Technologies*. <https://doi.org/10.1007/s10639-025-13316-y>.

Noever, D. and McKee, F. (2022). "Chatbots as problem solvers: Playing twenty questions with role Reversals," *arXiv.org*. <https://doi.org/10.48550/arXiv.2301.01743>.

Xu, X. (2024). "Innovative Role-Play Strategies in Business Ethics Education: The ChatGPT Approach," *International Journal of Higher Education* 13(1), 30-41. <https://doi.org/10.5430/ijhe.v13n1p30>.

Vecchiarini, M. and Somià, T. (2023). "Redefining entrepreneurship education in the age of artificial intelligence: An explorative analysis," *The International Journal of Management Education* 21(3), 1472-8117. <https://doi.org/10.1016/j.ijme.2023.100879>.

TRANSFORMING BUSINESS EDUCATION WITH AI: THREE CASE STUDIES

Alkis Vazacopoulos

Stevens Institute of Technology

Keywords: Artificial intelligence, large language model, learning experience, business education.

Abstract

The integration of generative AI and large language model (LLM) assistants is redefining the landscape of business education. This transformation is not theoretical—it is already happening through the use of innovative platforms that empower students and educators alike. This presentation explores three case studies that demonstrate how AI tools can significantly enhance the learning experience across different business school domains.

In a strategy course, **NotebookLM** acts as a dynamic thinking companion. Students upload readings, case materials, and lecture notes, which the system then synthesizes into mind maps, thematic summaries, and interactive study aids. Beyond static note-taking, students uncover hidden patterns across multiple strategic frameworks and business cases. This facilitates deeper understanding and encourages the construction of integrated knowledge systems—perfect for analyzing complex, multidimensional business problems.

For any course involving data analysis—from marketing to operations—**Julius.ai** democratizes access to exploratory data analytics. Students upload structured datasets and, through natural language prompts, generate visualizations, test hypotheses, and build predictive models without writing code. Instructors can use Julius.ai to teach real-world data interpretation skills while lowering technical barriers, making data literacy accessible to both technical and non-technical learners.

In operations management courses, **Bolt.new** empowers students to build simulations and test operational strategies through code-based experimentation. This browser-based platform allows learners to model inventory systems, queuing processes, or supply chain networks in real time. With built-in collaboration and AI support, students iterate quickly, bridging the gap between theoretical frameworks and practical implementation. Bolt.new enables experiential learning where students become not just consumers of knowledge but creators of systems.

EXPLORING THE IMPACT OF DIGITAL TRANSFORMATION ON EDUCATION AND INCLUSIVITY

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Keywords: Digital transformation, assistive technologies, educational innovation.

Introduction and Scope of Study

Digital transformation has emerged as a fundamental driver of change across various industries, shaping operational paradigms and redefining stakeholder interactions. While businesses have widely adopted digital strategies to enhance competitiveness and resilience, the field of education has been slower to integrate these innovations into pedagogical models. This paper critically examines how digital transformation can foster inclusivity in educational settings, particularly for learners with disabilities, and proposes specific, actionable strategies for implementation. By addressing gaps in the literature, clarifying key terms, and defining a structured methodological approach, this study provides a novel perspective on the intersection of digital innovation and inclusive education.

Literature Review and Contextual Background

The existing scholarship on digital transformation in education encompasses a broad range of themes, including the impact of artificial intelligence (AI) on personalized learning, the role of virtual and augmented reality in enhancing student engagement, and the effectiveness of assistive technologies in supporting diverse learners. Despite these advancements, a critical gap persists in the literature regarding the integration of a comprehensive framework that prioritizes inclusivity across various educational contexts (Alsobhi & Alyoubi, 2019; Aditya, Ferdiana & Kusumawardani, 2021). This study aims to develop a holistic digital transformation model that fosters accessibility and equity within the educational landscape, drawing upon prior research that integrates perspectives from technology, pedagogy, and policy.

Although the literature acknowledges the transformative potential of digital technologies in education, limited attention has been given to their role in promoting inclusivity. Benavides et al. (2020) highlight the complex interrelationships among stakeholders within higher education institutions (HEIs) undergoing digital transformation but note that inclusivity is often not a primary focus. Similarly, Mhlanga and Moloi (2020) emphasize how the COVID-19 pandemic has accelerated the evaluation of educational technologies, underscoring the necessity of a more effective integration that extends beyond mere access to technology. Furthermore, while digital education escalated during the pandemic, it remains unclear how effective these transformations have been in meeting diverse student needs and ensuring equitable access to resources (Eri et al., 2021). These findings suggest that a comprehensive framework is essential for ensuring inclusivity within digital transformation initiatives.

Also, research underscores the significance of teacher competencies in navigating digital transformation while fostering inclusive education. The European Digital

Competence Framework for Educators (Caena & Redecker, 2019) provides adaptable guidelines for educators to manage evolving technological landscapes. However, its primary focus on adaptation does not sufficiently address the advancement of inclusivity, indicating a critical area for further development. Inclusive digital education environments are essential for integrating individuals from diverse backgrounds into the learning process. Despite these insights, a cohesive application of inclusive digital transformation strategies remains underexplored.

Additionally, while existing studies highlight the potential of digital technologies to enhance accessibility and engagement, they often fail to articulate how these tools can specifically improve educational outcomes for underrepresented groups. A theoretical foundation is necessary to ensure that digital transformation drives effective educational performance (Shenkoya & Kim, 2023). However, many initiatives lack a structured implementation roadmap that emphasizes equity (Bong & Chen, 2021). Moreover, Ochieng and Gyasi (2021) examine the role of open educational resources, emphasizing their potential to advance social justice and equity in education. Their findings align with the broader need for a structured and inclusive digital transformation framework.

Defining Key Concepts

To ensure conceptual clarity, this paper adopts the following definitions:

Digital transformation refers to the integration of digital technologies into organizational processes to enhance efficiency, foster innovation, and improve adaptability. In education, this involves utilizing AI, big data, and immersive technologies to optimize learning experiences. Inclusivity in education is the practice of designing learning environments that accommodate diverse needs, ensuring all students—including those with disabilities—have equal access to resources, tools, and opportunities. Assistive technologies comprise digital tools that support students with disabilities in their learning process, such as speech-to-text software, screen readers, and adaptive communication devices.

Methodology

This study employed a qualitative research design grounded in auto-ethnographic reports from educators and focus group discussions with educational policymakers and technology developers. The methodological framework was inspired by Learmonth & Humphreys (2012), emphasizing reflective narratives to capture experiential insights. Data were collected from 20 educators across primary, secondary, and higher education institutions, each of whom had integrated digital tools into their teaching practices. Thematic analysis was applied to identify patterns in how digital transformation influences inclusive education.

Findings and Analysis

The study's findings highlighted several critical themes. Firstly, AI-powered learning management systems enable customized learning pathways, catering to students with different cognitive and physical abilities. For example, adaptive learning platforms such as DreamBox and Carnegie Learning adjust instructional content based on real-time student performance data. Also, virtual reality (VR) and augmented

reality (AR) have shown promise in enhancing engagement among students with learning disabilities. Studies indicate that immersive simulations improve comprehension and retention for students with autism spectrum disorder (Chen et al., 2015). Additionally, despite its potential, digital transformation in education faces barriers, including inadequate teacher training, lack of institutional support, and financial constraints. Survey data reveal that 65% of educators perceive a significant skills gap in effectively integrating digital tools into their teaching. Indeed, effective digital transformation requires alignment with inclusive education policies. Countries that have adopted comprehensive frameworks—such as the United Kingdom’s ‘EdTech Strategy’—demonstrate higher success rates in scaling digital inclusion initiatives.

Recommendations

Based on the findings, the following recommendations are proposed: Institutions should implement targeted professional development programs to enhance educators’ digital literacy. Governments and accreditation bodies must enforce universal design principles in digital education resources to ensure accessibility for all learners. Additionally, collaboration among educational institutions, technology firms, and policymakers can drive the development of cost-effective assistive technologies. Furthermore, funding mechanisms—such as grants for EdTech startups focused on inclusivity—can accelerate technological advancements. Finally, the continuous evaluation of digital transformation initiatives through user feedback and performance metrics is crucial for sustained progress.

Conclusion

Digital transformation presents a transformative opportunity to bridge accessibility gaps in education, enabling more inclusive learning environments. This study contributes to the existing body of knowledge by presenting an integrated framework that combines technological innovation with pedagogical inclusivity. Moving forward, a collaborative approach involving educators, policymakers, and technologists will be crucial in leveraging digital transformation to create equitable educational ecosystems.

References

- Aditya, B., Ferdiana, R., & Kusumawardani, S. (2021). A barrier diagnostic framework in process of digital transformation in higher education institutions. *Journal of Applied Research in Higher Education*, 14(2), 749-761.
- Alsobhi, A. and Alyoubi, K. (2019). Adaptation algorithms for selecting personalised learning experience based on learning style and dyslexia type. *Data Technologies and Applications*, 53(2), 189-200.
- Ari, R., Altınay, Z., Altınay, F., Dağlı, G., & Ari, E. (2022). Sustainable management and policies: the roles of stakeholders in the practice of inclusive education in digital transformation. *Electronics*, 11(4), 585.
- Benavides, L., Arias, J., Serna, M., Branch, J., & Burgos, D. (2020). Digital transformation in higher education institutions: a systematic literature review. *Sensors*, 20(11), 3291.

Bong, W. and Chen, W. (2021). Increasing faculty's competence in digital accessibility for inclusive education: a systematic literature review. *International Journal of Inclusive Education*, 28(2), 197-213.

Caena, F. and Redecker, C. (2019). Aligning teacher competence frameworks to 21st century challenges: the case for the european digital competence framework for educators (digcompedu). *European Journal of Education*, 54(3), 356-369.

Mhlanga, D. and Moloi, T. (2020). Covid-19 and the digital transformation of education: what are we learning on 4ir in south africa?. *Education Sciences*, 10(7), 180.

Ochieng, V. and Gyasi, R. (2021). Open educational resources and social justice: potentials and implications for research productivity in higher educational institutions. *E-Learning and Digital Media*, 18(2), 105-124.

Shenkoya, T. and Kim, E. (2023). Sustainability in higher education: digital transformation of the fourth industrial revolution and its impact on open knowledge. *Sustainability*, 15(3), 2473.

BRIDGING EXPERIENTIAL LEARNING AND AI IN MANAGEMENT EDUCATION: RESEARCH ON TRUST LITERACY AND STRUCTURED FRAMEWORKS

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Keywords: Management education, trust, AI literacy, RACE framework (Role, Action, Context, Explanation), ethical awareness.

Proposal

The integration of Artificial Intelligence (AI) in management education is becoming increasingly essential as organizations adopt AI-driven tools for collaboration and decision-making. While traditional Organizational Behavior (OB) courses focus on managing human dynamics, decision-making, and leadership, the inclusion of Generative AI (GAI) provides opportunities to bridge human and technological interaction, fostering both technical literacy and ethical awareness.

This paper explores the integration of experiential learning and GAI within management education, particularly in OB courses. We introduce important topics like trust, AI literacy, and the RACE framework (Role, Action, Context, Explanation), which are pertinent to modern educational practices. We present our experience conducted in Organizational Behavior (OB) courses in 2023 and 2024 and includes findings from two studies respectively. The 2023 study investigated trust and AI literacy within human-GAI teams during a semester-long project, highlighting the dynamics of trust formation, its predictors, and implications for collaboration. The 2024 study focuses on applying the RACE framework (Role, Action, Context, Explanation) to guide AI interactions, emphasizing critical, ethical, and reflective use. Together, these studies illustrate a progression in integrating AI tools into OB education and beyond, equipping students with essential skills for future workplaces. This paper demonstrates the use of experiential method in classroom environments, it provides insights into challenges faced during the implementation, how they were addressed, and more over we offer guidelines to management educators looking to adopt similar approaches.

To offer valuable insights into how GAI can enhance experiential learning and ethical awareness in management education we connect our experience to established experiential learning theories such as Kolb's Experiential Learning Cycle.

The Beginning 2023: Trust Literacy in Human-GAI collaboration

The adoption of AI technologies, especially generative GAI, including large language models (LLMs)—defined as systems that generate new content and solutions based on their training data (Noy & Zhang, 2023)—is rapidly expanding within organizations and teams (Pan & Froese, 2023). Recognized as a "general-purpose technology," GAI is increasingly embedded into organizational and team workflows (Cockburn et al., 2019). This growing integration underscores the importance of fostering effective collaboration between human and AI systems to enhance individual, team, and organizational performance (Wilson & Daugherty, 2018).

The growing use of GAI in teams has highlighted the need for AI literacy, which involves understanding AI concepts, recognizing its applications, and evaluating its societal impact (Long & Magerko, 2020; Verman & Singh, 2022). AI literacy is a dynamic, non-uniform skill set that varies across user groups (Benlian et al., 2022; Meske & Bunde, 2020), with several frameworks exploring its learning methods, components, and effects (Pinski & Benlian, 2024).

The first study took place in four sections of Organizational Behavior course during Fall 2023. A total of 122 students, primarily first-year students majoring in Business or Computer Science and Business, were registered in these sections. The 2023 study employed a multi-method approach. Qualitative data from team discussions and project reflections were analyzed to identify themes related to trust in GAI. For qualitative data analysis, inductive coding using the constant comparative method (Creswell & Creswell, 2017) was applied to examine students' perspectives and trust in GAI as a teammate.

The first study took place in four sections of Organizational Behavior course during Fall 2023. This course, which focuses on the study of individual and group behavior in organizational settings, is a core component of the Business College. A total of 122 students, primarily first-year students majoring in Business or Computer Science and Business, were registered in these sections. The course spanned 15 weeks, with classes held twice a week for 70 minutes each session.

The 2023 study employed a multi-method approach. Qualitative data from team discussions and project reflections were analyzed to identify themes related to trust in GAI. For qualitative data analysis, inductive coding using the constant comparative method (Creswell & Creswell, 2017) was applied to examine students' perspectives and trust in GAI as a teammate.

For this study, we adopted Long and Magerko's (2020) framework, which emphasizes understanding AI's fundamentals, its role in daily activities, and its societal implications. This approach aligns with our focus on enabling informed decision-making and effective human-GAI collaboration while addressing AI-specific features like autonomy and complexity (Wagner, 2021; Berente et al., 2021).

The last 3 weeks of the classes (week 13-15) each team member completed the survey about their AI literacy, trust in GAI during human-GAI interaction, and their perceptions of GAI as teammates in group projects. Of the surveys that were distributed, 116 students nested in 23 teams returned completed surveys (95% response rate). For the quantitative data, the pre- and post-surveys consisted of three constructs: AI literacy skills, prompt literacy skills, and perceptions of AI as a collaborator. The construct measuring AI literacy skills was adapted from Carolus et al. (2023) and included nine Likert scale items, demonstrating a reliability score of .89. An example item is: "I can identify ethical issues surrounding generative AI;" and "I know how to access generative AI tools in my project/work." The prompt literacy skills construct was adapted from Chen et al. (2024) and comprised seven Likert scale items (Cronbach $\alpha = .90$), designed to assess participants' ability to interact effectively with AI systems through prompts. Example item includes: "I know some strategies of prompt designing when interacting with generative AI." All items across the constructs were rated on a 5-point Likert scale, ranging from 1 ("very true") to 5 ("not at all true"). Data collection adhered to ethical research

standards, with consent obtained from all participants.

2023 Key Findings: First, trust in GAI was complex and categorized into trust, distrust, and ambivalence. While many students appreciated the accuracy and utility of AI in specific tasks, others expressed concerns about biases and limitations. Second, AI literacy emerged as a critical predictor of trust. Students with a stronger understanding of AI tools were more confident in their collaborative use. However, the study also revealed a paradox: higher AI literacy sometimes led to increased skepticism, as students became more aware of AI's potential risks and ethical challenges. These findings underscored the importance of targeted AI literacy programs to address knowledge gaps and foster effective human-GAI collaboration. By exploring the multifaceted nature of trust, the study laid a foundation for the next phase of integration in OB education. Figure 1 presents the distribution on participants' trust in GAI as a teammate.

Implications: The findings emphasize the importance of implementing targeted instructional strategies to address trust dynamics, AI literacy, and ethical considerations in human-AI collaboration. Educators can cultivate trust by incorporating GAI into specific, well-defined tasks where its utility and accuracy are evident, while also fostering critical engagement through structured activities that highlight its limitations and potential biases. To address the paradox where higher AI literacy may lead to hesitation, instructional approaches should encourage reflective discussions and the use of frameworks like RACE to guide ethical and effective AI use. By providing opportunities for hands-on experimentation and critical evaluation, educators can help students develop a balanced understanding of AI's capabilities, limitations, and role in collaborative learning environments.

2024 Advancing the vision: applying the Race framework for ethical and reflective AI use

Building on the insights from 2023, the OB course in 2024 introduced the RACE framework (Role, Action, Context, Explanation), a structured approach designed to guide ethical and reflective AI interactions. This framework helps students define their roles, understand AI's actions, consider the broader context, and explain decisions critically. A new focus on prompt engineering further allowed students to refine their skills in leveraging AI for decision-making. Students presented this reflective poster on the last day of the class.

The second study, with initial data collected through a survey administered at the beginning of the Fall 2024 semester to capture students' perspectives on AI, like the 2023 survey. A second survey took place in December 2024 to evaluate students' experiences and reflections after completing the course. For the second survey, in addition to items on trust and AI literacy, eight open-ended questions were included to explore participants' critical thinking skills, ethical considerations regarding collaboration with AI tools, and their application of the RACE framework. Example questions include: "How do you structure your prompts when asking ChatGPT about OB concepts?" and "How do you ensure your prompt aligns with the OB topic you're exploring (e.g., motivation, team dynamics, organizational culture)?"

Findings: A paired-sample t-test was conducted to evaluate the effect of the experiential learning on AI literacy and prompt literacy (see table 1). Results showed

a statistically significant increase in AI literacy scores from pretest ($M = 3.96$, $SD = 0.61$) to posttest ($M = 4.51$, $SD = .54$), $t(105) = 7.95$, $p < .001$, with a medium-to-large effect size ($d = .77$). Similarly, prompt literacy scores increased significantly from pretest ($M = 3.27$, $SD = .89$) to posttest ($M = 4.22$, $SD = 0.69$), $t(103) = 10.82$, $p < .001$, with a large effect size ($d = 1.06$). These findings suggest the experiential learning was effective in improving participants' AI and prompt literacy skills.

The qualitative analysis reveals students' varied trust in GAI, with many refining prompts to align AI responses with OB frameworks like motivation theories, job performance dimensions, and leadership models. Students assessed AI-generated responses for accuracy and relevance, often using follow-up questions to deepen understanding. Effective interactions showed that structured, iterative engagement with ChatGPT enhanced their grasp of OB concepts, particularly in team projects and case studies.

The journey of integrating AI into OB education demonstrates how trust, literacy, and structured frameworks can complement each other to enhance experiential learning. By bridging traditional management principles with cutting-edge AI technology, this narrative offers a roadmap for educators seeking to prepare students for an AI-driven future.

Based on Kolb's framework, we will propose specific instructional strategies to help educators adopt our example. These include designing hands-on AI activities for concrete experiences, using structured reflection prompts to guide observation, connecting AI interactions to theoretical concepts for abstract conceptualization, and encouraging iterative experimentation through real-world applications.

References

- Abdulwaded, M., & Nagy, K. Z. (2009). Applying Kolb's experiential learning cycle for laboratory education. *Journal of Engineering Education*, 98(3), 283-294.
- Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). MAILS-Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change-and meta-competencies. *Computers in Human Behavior: Artificial Humans*, 1(2), 100014.
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1). <https://doi.org/10.1186/s41239-023-00411-8>
- Chen, X., Pan, Z., & Jiang, Z. (2024). Exploring artificial intelligence (AI) literacy and prompt literacy: What do we know about artificial intelligence competency for educators?. In J. Cohen & G. Solano (Eds.), *Proceedings of Society for Information Technology & Teacher Education International Conference* (pp. 713-718). Las Vegas, Nevada, United States: Association for the Advancement of Computing in Education (AACE).
- Cockburn, I., Henderson, R., & Stern, S. (2019). The impact of artificial intelligence on innovation: An exploratory analysis. In *The University of Chicago Press*. <https://doi.org/10.7208/chicago/9780226613475.003.0004>
- Creswell, J.W., & Creswell, J.D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Thousand Oaks, CA: SAGE

Publications.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1-14. <https://doi.org/10.1145/3313831.3376727>

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654), 187-192. <https://doi.org/10.1126/science.adh2586>

Pan, Y., & Froese, F. J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human resource management review*, 33(1), 100924. <https://doi.org/10.1016/j.hrmr.2022.100924>

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*. ISBN: 978-1633693869

Session S1

FINTECH IN THE AI ERA

Chair: Steve Yang, Stevens Institute of Technology, USA

AMM APPLICATIONS TO CENTRALIZED MARKETS

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Keywords: AMM, target weighted ETF, liquidity providers, DEFI, decentralized finance.

ETFs and their mechanics

Some of the most popular investment instruments today are Exchanged Traded Funds (ETFs). According to the quarterly reports from the Securities Industry and Financial Markets Association (SIFMA), in the Q1 of 2024 US equity averaged 11.8 billion shares traded daily, out of which ETF shares numbered 2.4 billion shares. That is, 20.4% of the total number of shares traded are shares of ETF. According to statistics published by “Statista” in February 2023 the total value of ETF’s assets under management worldwide grew from 200 billion in 2002 to almost 10 trillion in 2022. In a survey of ETF executives, they anticipate that global Asset Under Management value will reach 18 trillion by the end of 2026.

What makes ETFs so successful? First, it allows small retail investors to purchase a portfolio of assets paying just a fraction of the sum needed to hold all underlying assets. This is primarily due to bid/ask spread and quantity traded. Specifically, to acquire portfolio assets, one needs to pay the ask cost of all components, while using an ETF one only pays the ask for one asset - the ETF. The ETF also allows trading much smaller proportional quantities. Second, the ETF issuer creates a primary market for the ETF. This allows Authorized Participants (APs) to trade in two secondary markets instead of just one in the ETF components. The APs are making two markets thus earn two spreads. Third, there is a strong documented relationship between turbulent times as measured by increase in market volatility and ETF investments. Some literature mentions that investors increase ETF investments in uncertain times due to the diversified nature of ETFs. Others mention that ETFs themselves contribute to an increase in correlation of assets, thus increasing market volatility. A recent survey of literature is Liebi (2020). Regardless, ETFs are an important tool in asset management.

AMM mechanics

An Automated Market Maker or AMM is a simple computer algorithm designed to facilitate exchange of cryptocurrencies while maintaining a stable relative market value. Although designed for the cryptocurrency exchange, the AMM design works with any type of assets as long as these assets are “tokenized”. In traditional finance, regular shares issued by a certain company can be thought of as tokens representing ownership in the company. Units of bonds \$1000 face value, may be thought of as tokens with an added complexity related to the maturity of the bond.

Retail clients can use an AMM to swap currency tokens located in liquidity pools. These assets are lent to the AMM by a special class of investors: the Liquidity Providers. These are investors who own large quantities of assets and deposit them

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into the pools. Being a liquidity provider (LP) allows passively earning fees paid by swappers to compensate for the potential loss of asset value.

The traditional AMM design allows constructing a pool of two or more assets and facilitates swapping between these assets. These designs have been extensively studied (see, e.g., Bichuch and Feinstein (2022)) with emphasis on their ability to act as a decentralized exchange. Within this work, in contrast, we view an AMM as a portfolio which is being rebalanced passively.

Immediate application. Target weighted Exchange Traded Fund (TETF)

A target weighted portfolio is any portfolio construction in which the fraction of the portfolio's wealth in any given, e.g, asset or sector is kept constant over time. Colloquially, a target weighted portfolio aims for these weights through periodic rebalancing. Target weighted portfolios are used extensively by financial advisors after determining their clients appetite for risk. For instance a client may be willing to take risks and thus the determined suitable allocation is 60% US equity and 40% US fixed income investments. Once determined, these allocations are only updated occasionally with, e.g., annual meetings. From these meetings, a financial advisor will construct a portfolio that is made up of different types of assets (e.g., equities and bonds) from different sectors (e.g., financials, energy and technology) in different geographic regions (e.g., developed and emerging markets).

On the other hand, when a client reviews his or her portfolio, two key metrics displayed up front are: (i) performance of the portfolio and (ii) the actual allocation as a high-level portfolio mix (e.g., between equities and fixed income). Therefore, at a high-level, a financial advisor's job is to simultaneously maximize the performance of a portfolio while maintaining the desired asset allocations.

However, maintaining target asset allocations can require frequent rebalancing of assets. As the asset prices fluctuate both intra- and inter-day, these portfolio weights drift from their targets. These fluctuations in the realized asset allocations are further complicated by complex correlations between returns. Therefore, though the target weights may only be reassessed infrequently, the actual rebalancing of the holdings needs to occur on much shorter timelines so as to not diverge from the clients desired position. Actively managing these portfolios to maintain the target weights, can be coupled with high fees from financial advisors and, for the client, hidden costs in (active) rebalancing.

In this work, we provide a novel formula for custom baskets so that an ETF can follow the published target weights as closely as possible. We call this construct a Target Weighted ETF (TETF). In our simulations, the TETF is able to passively maintain the target asset allocations. The ETF provider will produce custom rules to allow custom basket creation. These rules, through a simple arbitraging strategy, encourage AMM participants to rebalance the portfolio to maintain the target weights with minimal tracking error. Hereafter, this construction is called a Target Weighted ETF (TETF).

However, since the TETF provider allows its portfolio to be arbitrated in this way, the pure construction will dis-incentivize investment from clients, i.e., this rule will fail the regulations set out by the Securities and Exchange Commission to be in the best interest of the TETF holders. In order to compensate the TETF holders for

the costs associated with this arbitrage-taking, in-kind fees can be charged to market participants for any custom baskets used. This is done by distributing a fraction of the provided assets (when creating a creation unit (CU); similarly providing a fraction of the assets when redeeming a CU) to the TETF holdings. Following an optimized fee schedule, the APs will maintain the target weights with minimal mis-weighting while also systematically increasing the value of the TETF shares.

$$\ell = L \left(\alpha^* + \prod_{i=1}^N \left(\frac{(1 - \alpha^*)x_i + \Delta x_i}{x_i} \right)^{(1-\gamma)w_i} - 1 \right) \text{ for } \alpha^* = \min_{i=1, \dots, N} \frac{\Delta x_i}{x_i}$$

Figure 1: Mathematical construction of the custom basket rule providing the number of created CUs ℓ (redeemed if $\ell < 0$) for a TETF comprised of N distinct securities with target weights $(w_1, \dots, w_N) > 0$, current portfolio holdings $(x_1, \dots, x_N) > 0$, custom basket $(\Delta x_1, \dots, \Delta x_N)$ either positive (deposited) or negative (redeemed), outstanding TETF shares $L > 0$, and fee rate $\gamma \in [0, 1]$.

The mathematical structure for the TETF custom basket rule is provided in Figure 1.

In addition to allowing for any representative portfolio of the current ETF asset holdings, the TETF custom basket rule is designed to create arbitrage opportunities for the APs whenever the TETF's portfolio weights drift too far from the target weights. For instance, arbitrage opportunities are created for the APs if the relative weight between any two assets deviates by more than some fixed percentage from the target ratio. That is, the APs are incentivized to rebalance the TETF's holdings towards the target weights without any active participation of the TETF provider. The bounds on portfolio weights for when arbitrage opportunities exist are parameterized by a single variable $\gamma \in [0, 1]$, also referred to as the *fee rate*. This parameter γ functionally provides a bid-ask spread to the assets in CUs;¹¹ the lower the choice of the fee rate, the smaller the bid-ask spread and the lower the tolerance the TETF has for misweighting from the target weights. In particular, if $\gamma = 0$, we design the TETF to create arbitrage opportunities for the APs whenever the portfolio weights deviate at all from the targets; if $\gamma = 1$ then no arbitrage is offered to the APs at any level of misweighting. The fee rate parameterizes the TETF between these two extremes so that, e.g., misweightings are controlled while simultaneously not allowing the ETF portfolio to lose value to arbitraging by the APs.

We plan to run a historical experiment with a 60% equity and 40% fixed income portfolio.

References

Bichuch, M. and Z. Feinstein (2022). Axioms for automated market makers: A mathematical framework in fintech and decentralized finance. arXiv preprint arXiv:2210.01227 .

¹¹The fee rate γ is separate from the traditional fees collected by the TETF provider, such fees would be assessed as well.

Liebi, L. J. (2020). The effect of etfs on financial markets: a literature review. *Financial Markets and Portfolio Management* 34 (2), 165–178.

ML APPROACHES TO PDE MODELS IN FINANCE AND INSURANCE: A CRITICAL REVIEW

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Keywords: PDEs, finance, insurance, machine learning.

Abstract

Partial Differential Equation (PDE) models play a crucial role in various aspects of finance and insurance, providing a powerful alternative to simulation-based and purely data-driven approaches. In this presentation, we critically examine machine learning-based methods for solving PDE models commonly encountered in financial and insurance applications. We focus on three key approaches: (a) random feature models (RFM), (b) physics-informed neural networks (PINNs), and (c) Fredholm neural networks. Each of these leverages the underlying PDE structure of the problem to enhance modeling accuracy and efficiency. The discussion will be complemented with illustrative examples from risk management and insurance, highlighting the practical relevance of these methods.

RISK FACTOR PREMIUM THROUGH LLMs

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Keywords: GPT-o1, risk premium, large language model, OpenAI, asset pricing.

Introduction

Corporate 10-K filings disclose a wide range of risks in Item 1A, offering rich, unstructured information on firm-specific threats. Traditional asset pricing models, such as the Fama- French factors [1], often emphasize structured data (e.g., size, value) and may overlook these textual signals. Recent studies suggest that risks disclosed in regulatory filings can significantly affect asset returns [2, 3].

Advancements in Generative AI—particularly Large Language Models (LLMs)—now enable more effective extraction and interpretation of textual risk disclosures. Whereas classical topic modeling techniques (e.g., Latent Dirichlet Allocation, Probabilistic Latent Semantic Analysis) demand extensive tuning and produce less interpretable themes [4, 5, 6], LLMs can parse large volumes of text with prompts that elicit coherent, human-readable categories [7, 8]. Prompt-based frameworks have emerged as flexible solutions, capable of handling not just short text but also lengthier corporate disclosures with minimal manual intervention [9, 10, 11].

In this study, we adopt a multi-stage LLM-based approach to extract 19 interpretable risk categories from 10-K filings in the S&P1500 between 2015 and 2023. We then construct risk-neutral portfolios aligned with these risks and test whether they command statistically significant premia, both in a Fama-French five-factor setting and via cross-sectional Fama- MacBeth regressions [12]. Our findings suggest that certain constructed AI-derived risk factors exhibit robust risk premia, underscoring the importance of textual disclosures in contemporary asset pricing.

Data and methodology

We focus on Item 1A risk factor sections from S&P1500 firms over nine fiscal years (2015–2023). Company identifiers (ticker, CIK), fiscal years, and sector classifications are obtained from Wharton Research Data Services (WRDS), while daily and monthly stock prices come from Yahoo Finance. After filtering for valid tickers and data availability, our final sample comprises of 11,003 filings spread across eight sectors (materials, industrial, consumer discretionary, consumer staples, health care, financial, information technology, and communication services).

Each Item 1A section averages around 60,000 characters, making manual topic labeling impractical. We therefore employ a LLM-based approach to scale efficiently. Additional firm-level data (e.g., market capitalization, asset growth) facilitate the construction of Fama- French factors and allow us to control for size, value, profitability, and investment effects.

LLM Prompt-Based Risk Factor Topic Modeling Framework

We adopt a three-stage parallel-prompting framework for topic modeling [9, 11], beginning with filing-specific topic extraction, in which LLM processes each 10-K's Item 1A in parallel and assigns decimal proportions to multiple topics (summing

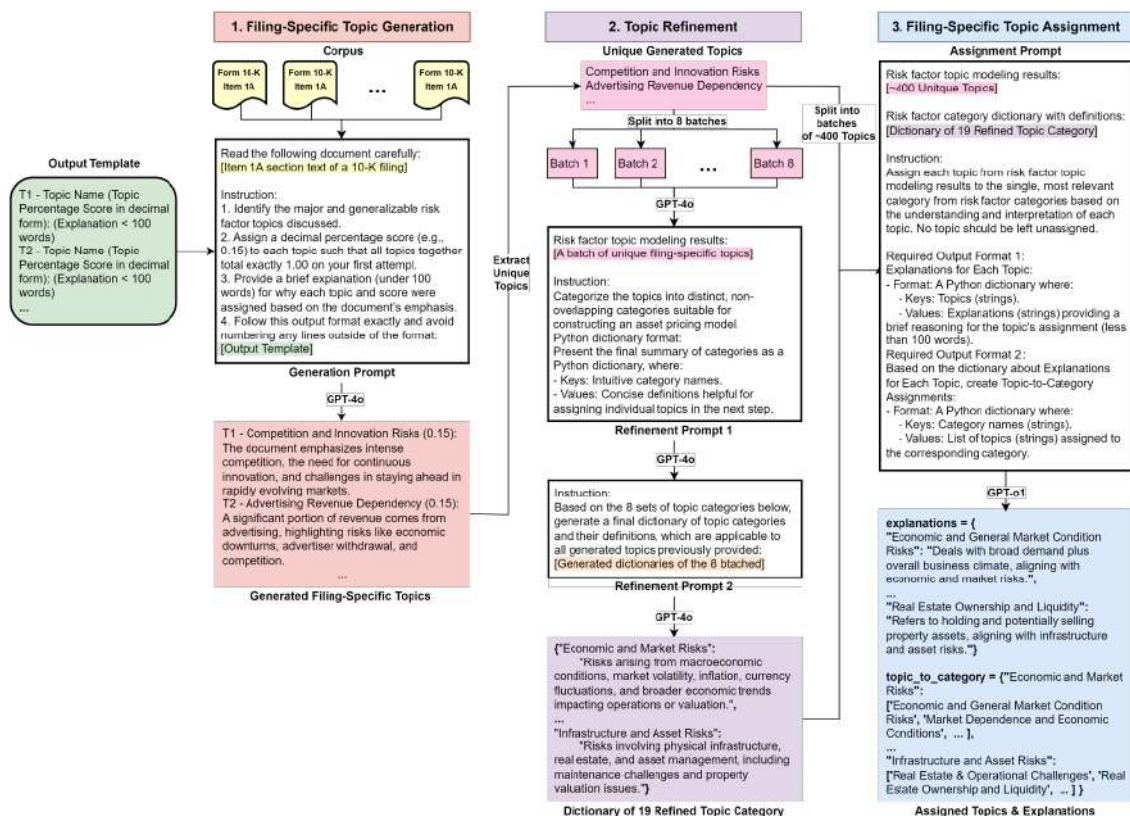


Figure 1: GPT Prompt-Based Topic Modeling Framework

to 1) to yield a granular representation of each firm's risk disclosures. Next, in the topic refinement stage, we aggregate and de-duplicate the initially extracted topics—often numbering in the tens of thousands—merging them into 19 higher-level risk categories (e.g., “Regulatory and Compliance Risks,” “Product and Innovation Risks,” “Health and Pandemic Risks”). Finally, during topic assignment, each granular topic is mapped to its most relevant category, and its proportion is merged into the category's score, thus preserving interpretability and consistency across filings while producing a firm-level risk score for each of the 19 categories.

Portfolio Construction

To assess whether these textual risk topics can generate risk premia, we adopt a portfolio-based approach. For each fiscal year and sector, we sort stocks into three volatility groups (based on the standard deviation of daily returns) and then further subdivide each volatility group into quintiles based on the scaled risk topic proportions for a particular risk category. We form risk-neutral RiskFactor_{*i*} portfolios by taking a long position in the riskiest quintile and a short position in the least risky quintile within each volatility group. We repeat this procedure for all 19 risk categories, generating RiskFactor1 through RiskFactor19.

Time-Series (Fama-French) and Cross-Sectional (Fama-MacBeth) Regressions

$RiskFactor_{i,sec_t} = \alpha_{RiskFactor_i} + \beta_1(R_m - R_f)_{sec_t} + \beta_2SMB_{sec_t} + \beta_3HML_{sec_t} + \beta_4RMW_{sec_t} + \beta_5CMA_{sec_t} + \epsilon_t$, where $i = 1, 2, \dots, 19$.

We regress each RiskFactor_{*i*} on the Fama-French five factors—market excess return (R_M), size (SMB), value (HML), profitability (RMW), and investment

(*CMA*)—to identify any unexplained risk-adjusted premium.

$R_t = b_0 + b_1 * SMB_{sec_t} + b_2 * HML_{sec_t} + b_3 * RMW_{sec_t} + b_4 * CMA_{sec_t} + b_5 * RiskFactor_{sec_{i,t}} + \epsilon_t$, where $i = 2, 12, 15$.

In a complementary analysis, we employ a Fama-MacBeth [12] cross-sectional approach, regressing individual stock returns on their estimated factor loadings to determine whether certain AI-extracted risk factors command a significant price of risk.

RiskFactor	significant Risk Factor name	coeff	p-values
2	Regulatory and Compliance Risks	0.0005	0.087*
12	Product and Innovation Risks	-0.0004	0.088*
15	Health and Pandemic Risks	-0.0005	0.013**

Table 1: Coefficients and p-values for various risk factors.

Key Findings

Significant Risk Disclosure Premium

Several RiskFactors show statistically significant risk-adjusted returns even after accounting for the standard Fama-French factors. For instance, based on Table 1, the health and pandemic factor tends to produce negative risk-adjusted returns, particularly post-2020, reflecting adverse impacts of COVID-19 pandemic uncertainty. By contrast, high regulatory and compliance risk appears to yield a positive premium, possibly due to increased scrutiny and barriers to entry that can deter lower-risk competitors.

Differential Return Effects

Regulatory & Compliance: Portfolios with high exposure to regulatory risks often earn a positive premium, suggesting the market compensates these firms for compliance burdens.

Product & Innovation: High product-innovation risk exposures correspond to lower risk-adjusted returns, indicating that ongoing R&D and innovation uncertainty may weigh on investor sentiment.

Health & Pandemic: Exposure to health-related risks is associated with underperformance post-2020, reflecting how heightened uncertainty around COVID-19 impacts returns.

Cross-Sectional Confirmation

Fama-MacBeth regressions confirm that certain risk factors remain significant while controlling for firm-level characteristics. It highlights that elevated product-innovation and pandemic-related risks reduce returns by 23.34% and 32.94% for every unit increase in such risks. These findings align with prior evidence of factor-specific premia and suggest that textual disclosures can capture risks not fully reflected in size, value, profitability, or investment factors.

Both in time-series and cross-sectional analyses, adding these risk factors often increases the adjusted R^2 , indicating stronger explanatory power for stock returns over the nine-year period studied.

Contributions and Implications

Variable	Model 1		Model 2	
	Coefficients	t-Statistics ^a	Coefficients	t-Statistics
Intercept	0.0008	5.910***	0.0006	4.691***
SMB	0.3852	2.135**	0.2120	1.045
HML	0.1377	0.960	0.0787	0.491
RMW	0.0481	0.675	0.1691	1.563
CMA	-0.1094	-0.934	-0.2317	-1.465
RiskFactor2			0.0227	0.182
RiskFactor12			-0.2334	-1.647*
RiskFactor15			-0.3294	-1.997**
Adj. R^2	0.927		0.931	
F-Statistic	226.3		138.7	
Observations	72		72	

^a ** and * denote significance at the 5% and 10% levels respectively.

Table 2: Fama-MacBeth cross-sectional regression estimation result comparison.

We present an LLM-based framework that processes large volumes of regulatory text, integrating textual risk disclosures into the traditional Fama-French factor model. This scalable, interpretable approach reveals distinct premia for regulatory compliance, product and innovation, and health and pandemic issues, mirroring the illiquidity premia insights of Amihud et al [2]. By converting unstructured language data into risk factors, our method can enhance portfolio construction and risk management decisions, allowing investors and analysts to better hedge or capitalize on evolving disclosures—particularly in sectors most vulnerable to regulatory or innovation uncertainties.

Conclusion and Future Directions

We document persistent, sector-specific return differentials linked to text-based risk topics, demonstrating that large-scale LLM-driven topic modeling can capture information not fully accounted for by traditional asset pricing factors. Our findings underscore the value of generative AI tools in systematically parsing extensive corporate disclosures, revealing new dimensions of systematic risk that warrant investor attention.

Future work may explore quarterly updates of textual risk premia based on both 10-Q and 10-K filings, examine interactions among multiple risk topics, and evaluate how LLM-driven sentiment analysis enhances risk factor-based portfolio construction. Additionally, we plan to compare our approach against traditional topic modeling techniques (e.g., LDA with PCA) and different large language models. Expanding to global markets or incorporating additional text sources, such as earnings call transcripts, could further validate the robustness of AI-driven risk factors in asset pricing.

References

- [1] E. F. Fama, K. R. French, Common risk factors in the returns on stocks and bonds, *Journal of financial economics* 33 (1) (1993) 3–56.

- [2] H. A. K. W. Z. H. Amihud, Y., The illiquidity premium: International evidence, SSRN Electronic Journal (2013).
- [3] I. F. Bank, M., Risk premium contributions of the fama and french mimicking factors, *Finance Research Letters* 29 (2018) 347–356.
- [4] D. M. Blei, A. Y. Ng, M. I. Jordan, Latent dirichlet allocation, *Journal of Machine Learning Research* 3 (Jan) (2003) 993–1022.
- [5] B. Zhang, S. Yang, Financial risk disclosure return premium: A topic modeling approach, In: *2024 IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr)*, 2024, pp. 1–6.
- [6] T. Hofmann, et al., Probabilistic latent semantic analysis., in: *UAI*, Vol. 99, 1999, pp. 289–296.
- [7] D. Newman, J. H. Lau, K. Grieser, T. Baldwin, Automatic evaluation of topic coherence, In: *Human language technologies: The 2010 annual conference of the North American chapter of the association for computational linguistics*, 2010, pp. 100–108.
- [8] M. Grootendorst, Bertopic: Neural topic modeling with a class-based tf-idf procedure, *arXiv preprint arXiv:2203.05794* (2022).
- [9] F. Bianchi, S. Terragni, D. Hovy, Pre-training is a hot topic: Contextualized document embeddings improve topic coherence, *arXiv preprint arXiv:2004.03974* (2020).
- [10] H. Wang, N. Prakash, N. K. Hoang, M. S. Hee, U. Naseem, R. K.-W. Lee, Prompting Large Language Models for Topic Modeling, *arXiv:2312.09693 [cs]* (Dec. 2023).
- [11] T. Doi, M. Isonuma, H. Yanaka, Topic Modeling for Short Texts with Large Language Models, in: *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 4: Student Research Workshop)*, Association for Computational Linguistics, Bangkok, Thailand, 2024, pp. 21–33.
- [12] C. M. Pham, A. Hoyle, S. Sun, P. Resnik, M. Iyyer, TopicGPT: A Prompt-based Topic Modeling Framework, *arXiv:2311.01449 [cs]* (Apr. 2024).
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A TECHNO-POLITICS PERSPECTIVE ON DIGITAL CURRENCIES: DIGITAL SOVEREIGNTY, SECURITY, AND GLOBAL FINANCIAL POWER

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Keywords: CBDCs, financial stability, national security, strategic autonomy.

Abstract

Central Bank Digital Currencies (CBDCs) represent a digital form of official currencies, issued and controlled by central banks, rather than physical cash or bank deposits. CBDCs have gained momentum as countries seek to modernize their financial systems in response to transformative technologies. However, CBDCs are not just a technological innovation; they are deeply political with the potential to reshape monetary systems and financial dominance. This necessitates acknowledging the role of security and navigating global financial competition, which influences geopolitical power, and highlights the possibility that CBDCs could shift financial influence and even be weaponized. Concerns over surveillance and control have prompted legislative responses (e.g., CBDC Anti-Surveillance State Act), reflecting fears that they could enable mass surveillance or state control, and reinforcing the idea that they are inherently dual-use technologies capable of empowering economies and serving as instruments of oversight. The risk of CBDCs being used for financial monitoring and control is not merely hypothetical but has become a genuine concern. On the one hand, they can result into a system free of counterparty risk, as central banks cannot default on their currency, eliminating the risk of bank failures and contributing to a more resilient financial system. On the other hand, they can be weaponized by, for instance, imposing conditions on payments, disrupting the financial systems of other nations, or manipulating international markets. Given the increasing role of CBDCs in global finance, it is crucial, therefore, to explore their implications for financial power, sovereignty, and security. This study aims to address the following research question:

How do CBDCs reshape global financial power dynamics, national sovereignty, and digital security, and what are the geopolitical implications of their adoption?

To address our research question, we examine the *technopolitical* implications of CBDCs as mechanisms of power and control. Through the lens of digital sovereignty, which highlights how control over digital infrastructures impacts national autonomy, governance, and international power dynamics, we explore how CBDCs i) intersect with these elements, ii) redefine power dynamics in global finance and security and iii) how *technopolitical* forces influence the diffusion of blockchain innovation, particularly for smaller nations. Digital sovereignty is primarily understood as a political and policy-driven practice rather than a strictly legal or organizational concept. Concerns over economic competitiveness, limited innovation capacity, reliance on foreign digital services, and challenges in ensuring strong cybersecurity have shaped the ongoing discourse on the topic. This discourse emphasizes the need to regain

control over digital infrastructure and technological production. By exploring these intersections, our work seeks to develop a novel theoretical framework for understanding how CBDCs impact power structures, governance, and national autonomy in the digital age.

Our study follows a structured methodological approach that integrates qualitative analysis with a case study. In doing so, we first, establish a theoretical framework by examining the intersection of CBDCs, digital sovereignty, financial stability, and geopolitical power. This involves a review of the existing literature and policy discussions, to understand CBDCs as instruments of both financial innovation and control. Next, we conduct a case study analysis of Norway, a country with an advanced digital infrastructure, and a history of financial innovation. This includes an examination of project documents, regulatory reports, and policy frameworks to assess how Norway balances national sovereignty, financial security, and interoperability with global financial systems. To further enrich our analysis, in-depth interviews with policymakers, financial regulators, and technology experts are conducted. These interviews provide insights into the strategic considerations behind CBDC implementations. Additionally, our study reviews policy debates and legislative measures to contextualize the potential risks and benefits associated with CBDCs. We then situate the experience of Norway within a global context by analyzing CBDC strategies in similarly technologically advanced nations. This assessment helps identify challenges, strategic priorities, and the geopolitical implications of digital currency adoption. Finally, we synthesize our findings to draw conclusions on how CBDCs influence financial sovereignty, global power structures, and security.

In doing so, our work provides a comprehensive *technopolitical* perspective on CBDCs, emphasizing their role as instruments of financial control and geopolitical influence rather than merely digital monetary tools. By analyzing their impact on national sovereignty, our work contributes to the debates on digital sovereignty, security, and the balance of financial power. Additionally, our work examines how CBDCs could challenge or reinforce existing financial hierarchies between dominant economies and emerging players. Our work also contributes to ongoing policy discussions and provides recommendations for navigating the transition to digital currencies. Our findings will also offer valuable policy insights, highlighting the risks and benefits of CBDC in areas of privacy, financial stability, and regulatory oversight.

Session S2

HEALTH ANALYTICS

Chair: John Kornak, University of California San Francisco, USA

STATISTICAL MODELING OF FMRI DATA FOR PRESURGICAL PLANNING

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Keywords: Bayesian modeling, fMRI data, decision theory.

Abstract

Over the past decade, neurosurgeons and neuroradiologists have increasingly relied on functional magnetic resonance imaging (fMRI) to assist in presurgical planning. fMRI helps identify brain regions responsible for specific tasks and has the potential to aid in presurgical and surgical brain mapping. The aim is for the surgeon to develop a tissue excision plan that spares critical brain areas, potentially leading to shorter surgeries and several positive outcomes. A shorter surgery translates to cost savings, reduced stress on the surgeon, and a lower risk of errors. For the patient, it means less stress, especially if they are awake during the procedure and required to perform tasks while the surgeon places an electrical probe on the brain until task disruption occurs. A marker is then placed on the disrupted area to guide the incision between markers.

A challenge with using fMRI for presurgical planning is the well-documented lack of reproducibility. Several steps in the fMRI analysis pipeline have been identified as possible contributors to this issue, including differences in scanners, scanning patients at different times of the day under varying conditions (e.g., after drinking coffee or not), and the vast number of preprocessing steps and analysis pipelines used. In this presentation, we focus on the analysis of fMRI data. The only preprocessing performed on the data before statistical analyses is the transformation from native "k-space" or spatial frequency domain to the image domain.

Two key requirements are necessary for using fMRI in presurgical planning: 1) spatial accuracy and 2) type II error control. Spatial smoothing is a crucial step in analyzing fMRI data. The standard method involves convolving the image data (at each time-series point) with a three-dimensional Gaussian kernel that applies a fixed amount of smoothing to the entire image. However, in presurgical planning, where spatial accuracy is paramount to determine functionally eloquent, peritumoral brain regions, global smoothing is contraindicated. Methods relying on global smoothing are not ideal as they can blur the boundaries between activated and non-activated brain regions. Moreover, while standard fMRI analysis calls for strict false positive control, pre-surgical planning emphasizes avoiding false negatives. A false negative might result in permanent damage to functionally critical brain regions.

In this talk, we present two Bayesian models that employ spatially adaptive smoothing to address the challenges posed by global smoothing. For both models, we start with the unsmoothed Z-statistic image obtained from standard software, such as SPM or FSL, and segment the image into three classes: deactivated, activated, and null. Both models smooth regions where appropriate but stop smoothing at the interface between null and activated (or deactivated) regions. The smoothing amount is determined locally based on the data. After fitting the data with our models, we apply a decision-theoretic approach to classify voxels. The models require

different loss functions, but both include a common component that differentially weights false positives and false negatives. This feature allows the user to specify the importance of false positives versus false negatives.

The first model is based on a nonparametric Potts prior model for image segmentation, which does not smooth over sharp boundaries in the Z-statistic image. The Potts model favors configurations where neighboring voxels belong to the same class. We assume three classes of voxels: activated (showing increased blood flow due to the task), null (where blood flow is unaffected), and deactivated (showing decreased blood flow due to the task). In a Potts model, the classes are modeled with parametric distributions. In our nonparametric Potts model, we model the classes nonparametrically using a mixture of Dirichlet process priors, one for each class of voxels. This allows for more flexible shapes of the class distributions. We use a Bayesian decision-theoretic approach to allocate voxels to each class, asymmetrically penalizing false negatives and false positives in the loss function.

Our second model is a spatially adaptive, conditionally autoregressive (CAR) model. Similar to the Potts model, it reduces smoothing at boundaries between activated and non-activated regions in the Z-statistic image. Spatial adaptivity is obtained by placing a CAR type prior on the variances as well as the means. To do so, we place a log-Gaussian prior on the variances and model the log variance using a CAR. After fitting the model to the data, we again apply a Bayesian decision-theoretic approach allowing different penalties for false negatives and positives.

We apply both models to presurgical fMRI data from a patient with an oligodendroglioma. The data come from a 32 year old woman, initially diagnosed after a seizure. The patient had persistent problems repeating phonemically challenging phrases. Prior to surgery she had an fMRI exam. The fMRI design consisted of an alternating on-off box car design where she was asked to silently recite challenging tongue twister phrase (on) followed by silent repetition of an unchallenging, rhythmic phoneme sequence (off). After surgery, histology confirmed an oligodendroglioma of the left inferior frontal and insular lobe. During surgery, electrical stimulation mapping (EMS) was performed to determine functionally eloquent, peritumoral regions responsible for speech. Postsurgery, our modeling results were assessed against EMS, showing promise for these models and fMRI in presurgical planning.

REPETITIVE HEAD IMPACT EXPOSURE AND CONCUSSION RISK: NOVEL MACHINE LEARNING/AI METHODS TO THE RESCUE

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Keywords: Time series, regularization techniques, functional data analysis, repetitive head impact exposure.

Abstract

Sport-related concussion (SRC) is a significant public health concern, accounting for over 200,000 emergency department visits annually in the United States. The biomechanical mechanism underlying SRC involves head impacts that generate high-magnitude rotational accelerations, which in turn contribute to brain injury. Increasing evidence from human studies suggests that repetitive head impact exposure (HIE) plays a crucial role in reducing SRC tolerance among contact sport athletes. However, previous research attempting to quantify the relationship between HIE and incident concussion has often relied on overly simplistic statistical methodologies, limiting the precision of findings and their applicability to clinical and preventative interventions.

The effect of HIE on concussion tolerance is likely influenced by several factors, including the magnitude, frequency, and cumulative number of head impacts sustained by an athlete. Higher-severity impacts, increased exposure, and greater frequency of impacts are thought to contribute to a reduction in concussion tolerance. However, the relationship between HIE and SRC is further complicated by the temporal variation in secondary injury responses and healing associated with 'subconcussive' impacts. Preclinical studies using rodent models have identified neuroinflammatory responses following mild injuries, even in the absence of significant behavioral deficits. Similar findings have been observed in human studies, where acute neuroinflammation has been detected following SRC. These observations suggest that repetitive, lower-magnitude head impacts may trigger neurophysiological changes that reduce an athlete's resilience to future concussions.

The identification of this secondary concussion mechanism has the potential to transform the fields of biomechanics, clinical management, and injury prevention. If HIE is shown to be a significant modifier of concussion tolerance, targeted interventions can be developed to mitigate risk. For example, team athletic trainers could monitor athletes with elevated HIE and implement corrective measures, such as refining playing techniques, limiting exposure through controlled practice drills, or temporarily removing high-risk players from contact activities. This proactive approach could significantly reduce SRC incidence and long-term neurological consequences in contact sport athletes.

Each head impact experienced by an athlete is characterized by multiple biomechanical measurements, including three-dimensional linear acceleration, rotational acceleration, and vector linear acceleration magnitude. These metrics are typically recorded within a 40-millisecond window around each impact event that exceeds a 10g threshold in magnitude. The rich dataset collected from these measurements en-

ables the extraction of a variety of features at multiple temporal scales, including per impact, daily exposure, and cumulative exposure over an entire sports season. To analyze these data, we employed unsupervised statistical learning methods to generate novel data-driven features, which were subsequently incorporated into functional regression models to predict SRC occurrence and its potential consequences.

Our preliminary analysis utilized data from the Concussion Assessment, Research, and Education (CARE) study, focusing on all reported concussions sustained during both the preseason and regular season. Findings indicated that approximately half of all SRCs occurred during the preseason (33 out of 68 recorded concussions). Furthermore, majority of concussions were sustained during practice sessions (33 in the preseason and 15 in the regular season), while only 19 occurred during competitive games. These data highlight the need for increased attention to HIE during practice sessions, as they represent a substantial portion of the concussion burden in collegiate football.

To further investigate the association between cumulative head impact exposure and SRC risk, we examined data collected from football players and their matched controls. Control-matching was performed iteratively, with 200 different matched datasets created to prevent reliance on a single set of controls. Using data from the CARE dataset, we identified 68 concussions and employed a nested case-control design, ensuring that each concussed athlete was matched to a control within the same team, season, practice period, and position category. Functional regression modeling revealed significant associations between cumulative within-day head impacts and the likelihood of sustaining a concussion on the injury day (Day 0) as well as 4 and 7 days prior to the injury event.

In addition to cumulative impact analysis, we applied statistical regularization approaches and functional data analytic techniques to incorporate additional biomechanical variables into our models. Key predictors of SRC included the location of impact, peak linear acceleration, peak rotational acceleration, area under the acceleration curve, number of peaks within each 40-millisecond impact interval, and principal component scores derived from the empirical functional principal component analysis (FPCA) decomposition of the 40-millisecond impact time series. To ensure model parsimony and predictive accuracy, we utilized the Least Absolute Shrinkage and Selection Operator (LASSO) regularization technique to extract the most informative features contributing to SRC risk.

Furthermore, we implemented penalized scalar-on-function regression models, where SRC occurrence served as the dependent variable and head impact characteristics observed during practice/game days and prior days served as predictors. For each analysis, controls were selected from the pool of non-injured athletes, allowing for robust model performance evaluation. Our approach incorporated state-of-the-art statistical methodologies, including Functional Generalized Additive Models (FGAM) and Variable-Domain Functional Regression (VDFR). Model performance was assessed via internal cross-validation, ensuring that predictions remained generalizable and robust across different athlete cohorts.

Beyond the prediction of SRC occurrence, we leveraged HIE features to develop functional regression models that predict post-SRC recovery trajectories. Recovery from SRC is highly individualized, influenced by multiple factors such as the severity

of the initial injury, the cumulative burden of previous head impacts, and the timing of medical intervention. Our models accounted for the full history of HIE exposure for each athlete, capturing both short-term and long-term dependencies. To address the challenge of uneven sampling intervals—where some athletes were evaluated at three-day intervals and others at ten-day intervals—we employed Variable-Domain Functional Regression. This approach allowed us to model the time-varying effects of HIE exposure on recovery outcomes while maintaining statistical rigor.

In conclusion, our study highlights the importance of advanced statistical methodologies in understanding the relationship between HIE and SRC risk. Traditional analytical approaches have largely failed to capture the complexity of biomechanical and neurophysiological interactions underlying concussion susceptibility. By integrating functional regression techniques, regularization methods, and machine learning-driven feature extraction, we provide a more comprehensive framework for predicting SRC occurrence and recovery. Our findings have significant implications for sports medicine, athletic training, and injury prevention strategies, paving the way for data-driven interventions aimed at reducing concussion risk in contact sports. Future research should focus on validating these models across diverse athletic populations and refining predictive algorithms to further enhance concussion prevention and management efforts.

INCREASING EFFICIENCY AND QUALITY OF CLINICAL CARE OPERATIONS WITH A LLM-BASED AGENT SYSTEM

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Keywords: Large language model, process optimization, AI agent, clinical documentation.

Introduction

The healthcare system is dedicated to maintaining the health and lives of individuals, with hospitals serving as a critical component, particularly for inpatient care. However, like in many European countries, the medical system in Germany faces increasing pressure due to a combination of factors, including a shortage of skilled workers, rising hospital costs, and aging populations. The German healthcare system is overburdened by these rising costs and the heavy workload of its employees. In Germany alone, approximately 16.8 million patients were treated as inpatients in 2022, with 1.38 million employees working in the hospital sector (Statistisches Bundesamt, 2025).

A significant portion of healthcare activities involves documenting actions to ensure continuity of patient support across shifts. This documentation is essential but can be excessive, with some studies indicating that shift documentation takes between 30 to 90 minutes per shift. This time expenditure, which can approximate an hour out of a seven-hour shift, contributes to the overall burden on healthcare professionals and nursing staff. (HIMSS Europe, 2015; Kazmarek et al., 2022).

Various applications of Large Language Models (LLMs) in clinical processes quickly arise, primarily in diagnostics or the interpretation of medical expert texts (Yu et al., 2024; Porter et al., 2024; Xuhai et al., 2024). Much of this research is still in its early stages. This research project report presents the result of a collaborative project between THI Business School and the Clinical Centre Ingolstadt. We present a LLM-based agent system that automatically generates human-readable shift reports using data collected during the shift. The system aims to generate standardized, easily readable, and error-proof reports. The goal is to reduce the time spent on care documentation between shifts by 70% while maintaining compliance with legal documentation requirements and clinical safety regulations. Contrary to many other research approaches, this paper does not emphasize the suitability of specific LLMs due to the constant and significant progress in this area. Instead, we focus on the application of LLM technology to implement the most efficient possible solution for our specific problem using techniques such as fine-tuning, that can be applied to any LLM.

Methodology

The methodology for developing the prototype of the AI agent system followed a structured approach, divided into several phases. Initially, the project goal was defined in collaboration with experienced nursing professionals, focusing on the needs of nursing staff in IMC (Intermediate Care) and Stroke Unit wards at the Clinical

Centre Ingolstadt. These units are characterized by high-intensity interdisciplinary patient care and extensive documentation requirements.

A key issue was the significant time burden associated with creating shift reports, which internal experts estimated to be between 56 and 76 minutes per shift. To gain a comprehensive overview of all issues related to shift report creation, a problem identification survey was conducted. The main problems included the high time expenditure, psychological stress due to mandatory documentation, poor report quality caused by linguistic issues and inconsistencies, as well as information gaps and redundancies.

The overarching goal of the project is the automatic generation of shift reports, focusing on four main categories: consciousness, breathing, mobility, and pain. Additionally, a summary of each patient's condition should be generated.

The technical solution concept was divided into four interconnected layers: user interaction (UI), system logic, data, and an AI layer implementing LLM. Initial tests were conducted using OpenAI's GPT-4o-mini model, yielding promising results (OpenAI, 2024). The selection of this LLM was based on its high benchmark scores in medical applications and its compatibility with the prototype's requirements (Zhou et al., 2023; Irugalbandara et al., 2024; Yao et al., 2024). Due to the sensitivity of medical data and to prepare for a later in-house deployment, a Meta Llama 3 model with 8 billion parameters was chosen for comparison (Chen et al., 2023a; Chen et al., 2023b).

The system logic was implemented as a central algorithm handling data preprocessing, interaction with the LLMs, and user communication. Since the Patient Data Management System (PDMS) did not have an automated export function, the dataset for training the LLMs was manually created by transcribing 3,800 data points for 100 patients. The dataset was structured to replicate the PDMS format and was split into training (80 patients) and testing (20 patients) phases. To ensure a static dataset for the prototype, the data was organized in a table format and simplified into average values for each shift.

Both LLMs required optimization through prompt engineering and fine-tuning. For fine-tuning, a dataset of 80 manually created summaries was combined with synthetically generated target output from ChatGPT-4o. The fine-tuned model showed improved adherence to the desired output format, though further fine-tuning with a larger dataset is recommended for optimal performance.

As a systemic problem, LLM-based applications may encounter issues with undesirable effects, such as hallucinations (Waldo et al., 2024; Huang et al., 2025). In our case, this could lead to incorrect interpretations of patient data, resulting in inaccurate recommendations for the next shift. During the initial stages of the pilot, this issue was addressed using human-in-the-loop technique: the output must be confirmed by a human before the report is saved. This approach also generates additional data for the supervised fine-tuning of the model. In addition, from a legal perspective, this process will be necessary due to the EU AI Act (European Union, 2024). From a technical standpoint, methods to prevent the generation of erroneous outputs are already being discussed, with careful fine-tuning being one of these methods (Huang et al., 2025). With a growing database of accurately evaluated data, we expect the system to be able to verify outputs using more advanced

algorithms to avoid incorrect results.

On the user interaction layer, a web application was developed, integrating with the existing PDMS interface. Key functionalities include selecting the shift type and patient, topic-specific report generation, detailed and accurate summaries based on available data, and the ability to edit and refine generated reports. An expert evaluation showed that the prototype generally meets the requirements but also highlighted potential areas for improvement.

Results

The initial results from the prototype are very promising. Even the relatively small Meta Llama-3.1-8B model produced very good results, but only after fine-tuning, whereas the OpenAI model delivered partially good results even without fine-tuning. Based on these findings, the project team decided to continue working with the Meta Llama-3.1-8B model. For the test sample, the results were fully satisfactory. The expert evaluation not only confirmed that the time reduction was significant but also found that 100% of the AI-generated shift reports contained all necessary information. In contrast, only 50% of the manually written shift reports were sufficiently complete. The next step is to expand the test with a larger sample size and further refine the fine-tuning of the model.

Discussion

Initial findings suggest significant potential for advancing clinical documentation, as standard documents can be efficiently generated using large language models (LLMs). The initial prototype required substantial manual effort and was therefore limited in scope. However, the promising results indicate that the prototype can now be expanded, and additional data should be generated for fine-tuning.

Due to legal requirements, human verification of LLM-generated content will remain necessary. Even if the model is well fine-tuned and does not tend to hallucinate, errors cannot be entirely ruled out.

These encouraging outcomes open up possibilities for further applications and improvements. For instance, by leveraging historical documentation, LLMs can enhance report quality - a task previously unmanageable due to manual time constraints. Moreover, LLMs are capable of interpreting subtle changes in patient history.

Additionally, with the increasing number of foreign nursing staff in the medical sector, multilingual training of the system could reduce misunderstandings and improve communication, allowing more time to be dedicated to direct patient care.

References

Chen, B., Shu, C., Shareghi, E., et. al. (2023a): FireAct: Toward Language Agent Fine-tuning, arXiv, doi: 10.48550/arXiv.2310.05915.

Chen, Z., Cano, A., Romanou, A., et. al. (2023b): MEDITRON-70B: Scaling Medical Pretraining for Large Language Models, arXiv, doi: 10.48550/ARXIV.2311.16079.

European Union (2024): Regulation (EU) 2024/1689 (EU AI Act), <https://eur-lex.europa.eu/eli/reg/2024/1689/oj/eng>.

- HIMSS Europe (2015): Nursing Handover Documentation Study, 2015, p. 9.
- Huang, L., Yu, W., Ma, W., Zhong, W., Feng, Z., Wang, H., Chen, Q., Peng, W., Feng, X., Qin, B. & Liu, T. (2025): A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions, in: *ACM Transactions on Information Systems*, Vol. 43, No. 2, p. 1–55.
- Irugalbandara, C., Mahendra, A., Daynauth, R., et. al. (2024): Scaling Down to Scale Up: A Cost-Benefit Analysis of Replacing OpenAI’s LLM with Open Source SLMs in Production, in: *2024 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS)*, Indianapolis, IN, USA: IEEE, p. 280–291, doi: 10.1109/ISPASS61541.2024.00034.
- Kaczmarek, S., Fiedler, M., Bongers, A., Wibbeling, S., and Grzeszick, R. (2022): Dataset and Methods for Recognizing Care Activities, in: *iWOAR ’22: 7th international Workshop on Sensor-based Activity Recognition and Artificial Intelligence*, September 19/20, 2022, Rostock, Germany. ACM, New York, NY, USA, doi: 10.1145/3558884.3558891.
- OpenAI (2024): GPT-4o mini: advancing cost-efficient intelligence, <https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence>.
- Porter, R., Diehl, A., et. al (2024): LLMD: A Large Language Model for Interpreting Longitudinal Medical Records. PicnicHealth, USA, San Francisco. Research Paper. <https://arxiv.org/pdf/2410.12860v1>.
- Shi, X., Liu, J., Liu, Y., Cheng, Q. & Lu, W. (2025): Know where to go: Make LLM a relevant, responsible, and trustworthy searchers, in: *Decision Support Systems*, Vol. 188, p. 114354.
- Statistisches Bundesamt (Destatis) (2025): Health / Hospitals. <https://www.destatis.de/EN/Themes/Society-Environment/Health/Hospitals>.
- Waldo, J.; Boussard, S. (2025): GPTs and Hallucination, in: *Communications of the ACM*, Vol. 68, No. 1, p. 40–45.
- Yu, H., Fan, L., Li, L., Zhou, J., Ma, Z., Xian, L. et al. (2024): Large Language Models in Biomedical and Health Informatics: A Review with Bibliometric Analysis, in: *Journal of Healthcare Informatics Research* 8 (4), p. 658–711. <https://doi.org/10.1007/s41666-024-00171-8>.
- Yao, Yifan; Duan, Jinhao; Xu, Kaidi; et. al. (2024): A survey on large language model (LLM) security and privacy: The Good, The Bad, and The Ugly, in: *High-Confidence Computing*, Vol. 4, No. 2, p. 100211, doi: 10.1016/j.hcc.2024.100211.
- Zhou, Hongjian; Liu, Fenglin; Gu, Boyang; et. al. (2023): A Survey of Large Language Models in Medicine: Progress, Application, and Challenge, *arXiv*, doi: 10.48550/ARXIV.2311.05112.
- Xuhai, X., Bingsheng Y., Yuanzhe D., Saadia G. et al. (2024): Mental-LLM: Leveraging Large Language Models for Mental Health Prediction via Online Text Data, in: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* Vol. 8, No. 1, Article 31, p. 1-32 (March 2024), <https://doi.org/10.1145/3643540>.

CROSS-SECTIONAL ESTIMATES IN MULTI-STATE MODELS WITH APPLICATIONS IN THE HIV CASCADE OF CARE

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Keywords: Multi-state models, cross-sectional estimates, HIV.

Abstract

We present a simple method which uses state occupation probabilities in the context of a prospective multi-state model to produce cross-sectional (retrospective) estimates of the proportion of a population residing in a particular state at a specific point in (calendar) time. Our approach takes the evolution of the state occupation probability function for each member of our cohort up to the time under consideration, and integrates over all cohort members (who, due to the staggered nature of joining the cohort, will be at a different part of their respective state occupation probability trajectory). We illustrate the methodology using prospectively collected routine clinical data from a large cohort of people living with HIV/AIDS receiving care and treatment services in Kenya, Uganda and Tanzania. Through this application we stress how established methods in multi-state models can be used to produce estimates via the use of routinely collected clinical data, which obviate the need for launching expensive and time-consuming cross-sectional epidemiological surveys. What is more, the size and coverage of our population is much higher than, for example, the population-based HIV Impact Assessments (PHIAs) in our catchment area, which cost millions and were done only once. By contrast, the analyses we present can be performed repeatedly over time with relatively minimal effort and expense.

While PHIA surveys provide critical nationally representative estimates of all three UNAIDS targets, their high cost prohibits routine and widespread implementation. Additionally, population-based surveys cannot provide reliable sub-national estimates needed to guide more precisely targeted funding decisions. In the Kenyan PHIA, the proportion of PLWH on ART for Uasin Gishu county was estimated from a sample of 24 individuals, while our analysis used data from 7771 PLWH enrolled at 11 clinics in that one county alone. At the same time, estimates based on routine clinical data cannot provide information on the first “90”. A good strategy would be to carry out national surveys periodically, followed by clinical cohort studies performed in the intervening period.

TOWARD MACHINE LEARNING WITH BAYESIAN IMAGE ANALYSIS IN TRANSFORMED SPACES

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Keywords: Bayesian image analysis, data-driven image analysis, Fourier space, transformed spaces, wavelets.

Abstract

Bayesian image analysis offers a principled framework for improving image quality by integrating prior knowledge about image characteristics with probabilistic models of noise and uncertainty. Traditional Bayesian image analysis is performed in the conventional image space, where modeling spatial dependencies and correlations presents significant computational challenges. In this presentation, we introduce an alternative paradigm—Bayesian image analysis in transformed spaces—where spatially correlated priors, which are complex to handle in image space, can be efficiently represented as independent processes in an appropriately chosen transformed domain. Specifically, we describe the Bayesian Image Analysis in Transformed Space (BITS) framework, which utilizes both Fourier and wavelet transforms to reformulate image priors and likelihoods. This reformulation allows for computationally efficient and scalable Bayesian inference by breaking down high-dimensional spatially correlated problems into a series of independent, one-dimensional estimation tasks.

Statistical image analysis encompasses a wide range of applications, including noise reduction, de-blurring, feature enhancement, and object detection. Bayesian methods provide a rigorous approach to solving these problems by incorporating domain knowledge into a probabilistic model. Traditional Bayesian models in image space, however, suffer from high dimensionality and complex interdependencies among neighboring pixels or regions. To address these challenges, we propose a reformulation of Bayesian image analysis in transformed spaces, where spatial correlations are modeled more efficiently. This transformation enables not only improved computational feasibility but also the ability to leverage data-driven approaches for prior specification.

We have previously demonstrated the utility of Fourier-space Bayesian modeling, where both the prior distribution and likelihood function are expressed in terms of spatial frequency components. In the Bayesian Image Analysis in Fourier Space (BIFS) framework, spatially correlated priors in image space are transformed into a set of independent processes across Fourier space. This transformation breaks the high-dimensional image estimation problem into a series of trivially parallelizable one-dimensional problems, dramatically enhancing computational efficiency. In conventional BIFS, prior distributions for the Fourier coefficients are specified analytically, using predefined models for the modulus and argument of the complex-valued signal at each frequency location. The flexibility of this approach allows for the

incorporation of known image properties, such as smoothness and edge-preserving characteristics, by appropriately defining prior distributions over spatial frequencies.

While analytical priors in Fourier space offer computational advantages, they may not always capture the full complexity of real-world images. To address this limitation, we introduce a data-driven approach (DD-BIFS) in which priors are learned empirically from a database of images. In the DD-BIFS framework, images are first transformed into Fourier space, and empirical distributions of Fourier coefficients are estimated at each frequency location. This results in parameter maps that describe the statistical properties of image frequency components based on real data, which are then used as priors in Bayesian image reconstruction. By leveraging large datasets, DD-BIFS allows for a more adaptive and robust modeling framework, particularly for applications in medical imaging where domain-specific priors are crucial for accurate image enhancement and interpretation.

Beyond Fourier-space modeling, wavelet transforms provide an alternative transformed space for Bayesian image analysis. Unlike Fourier transforms, which decompose an image into global frequency components, wavelet transforms offer a multi-scale representation that captures both spatial and frequency information. The Bayesian Image Analysis in Wavelet Space (BIWS) framework extends the principles of BIFS by defining priors over wavelet coefficients instead of Fourier coefficients. This allows for localized modeling of image structures, making it particularly effective for applications involving non-stationary image features, such as edges, textures, and anatomical structures in medical images.

A key advantage of Bayesian image analysis in transformed spaces is the computational efficiency gained through decomposition into independent processes. In both Fourier and wavelet domains, the originally high-dimensional and interdependent estimation problem in image space is converted into a set of smaller, independent estimation problems that can be solved in parallel. This property makes BITS highly scalable and suitable for modern machine learning architectures, including GPU-acceleration.

We demonstrate the practical impact of BITS through applications in medical imaging, particularly in the enhancement of arterial spin labeling (ASL) perfusion images using a database of human brain positron emission tomography (PET) images. In this application, DD-BIFS leverages prior knowledge derived from PET images to enhance ASL images, improving their signal-to-noise ratio and clinical interpretability. The results illustrate the potential of BITS to integrate domain-specific knowledge with data-driven learning in a computationally efficient manner.

The reformulation of Bayesian image analysis in transformed spaces presents a powerful alternative to conventional spatial-domain modeling, offering significant advantages in terms of computational efficiency, scalability, and adaptability to data-driven approaches. By leveraging Fourier and wavelet transforms, BITS provides a flexible framework for incorporating spatial priors and handling spatial dependencies in a mathematically tractable manner. As machine learning continues to evolve, the integration of Bayesian inference with transformed-space representations offers promising directions for advancing image analysis in diverse domains, from medical imaging to remote sensing and beyond.

RESEARCH COLLOQUIUM

Chair: Panos Repoussis, Athens University of Economics and Business,
Greece

INTANGIBLE ASSETS INVESTMENT AND FIRM INNOVATION PERFORMANCE: EVIDENCE FROM EUROPE

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Keywords: Intangible assets, innovation, firm.

Project

GLOBALINTO: Capturing the value of intangible assets in micro data to promote the EU's growth and competitiveness (Grant Agreement ID: 822259). The project duration is 1st of February 2019 – 30th of April 2022.

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Abstract

Intangible assets (IAs) are an essential ingredient of the firms' inventive capacity and crucial leverage for turning them into successful innovations and improving their business performance. However, the link between intangible assets and innovation has only been partially exploited and is often overlooked (Montressor and Vezzani, 2016, Zambon and Monciardini, 2015). Micro analysis of innovation primarily focuses on one or few intangibles at a time (e.g., Hall et al., 2013, Ciriaci, 2017), failing, in general, to recognize the "full" spectrum of intangible activities for increasing enterprise innovation performance (Montressor and Vezzani, 2016; Montressor and Vezzani, 2022; Thum-Thysen et al., 2017). Furthermore, the strategic importance of these investments and the patterns through which they are undertaken are not generally taken into account (Haskel and Westlake, 2018).

Although research and development (R&D) is a crucial innovation input, there are also other non-R&D intangibles providing firms with essential knowledge that supports and facilitates the different phases through which innovation eventually takes place as well as its different dimensions. The view of innovation as a system [e.g., Freeman (1988), Lundvall (1992), Nelson and Rosenberg (1993)] and the more recent open innovation approach (Chesbrough, 2003) have extensively contended

that the innovation process is much less "R&D centric" than the standard "linear model" and emphasized the importance of the transfer and diffusion of ideas, skills, knowledge, information, and signals of many kinds that are conducive to innovation: training, design, reputation, and branding, are just a few examples.

Rather unfortunately, the innovation analysis of intangibles so far has been theoretically guided by the R&D-based "knowledge production function" framework (Griliches, 1998) simply augmented with the inclusion of some other intangible assets (Montessor and Vezzani, 2016). Furthermore, the primary data source to empirically investigate intangibles' innovation impact was the Community Innovation Survey (CIS), the reference survey in Europe (Arundel and Smith, 2013), where intangibles are merely treated as activities that firms might engage in innovating (e.g., Garcia, 2011; Ciriaci, 2017). While direct costs related to innovation activities are essential, a focus on intangible assets investments offers a more comprehensive understanding of the factors influencing innovation, by acknowledging the complex nature of innovation and the significance of long-term, strategic investments in human, organizational, and intellectual capital. However, although the role of intangible assets in creating value in business firms is gradually recognized, significant challenges in measuring their value and contribution remain (Haskel and Westlake, 2018; Martin and Baybutt, 2021), and business surveys are relatively limited (Martin and Baybutt, 2021). As a result, intangible assets are usually narrowly understood/conceptualized and empirically studied in a compact/unpacked way by neglecting their heterogeneous nature and strategic importance in achieving sustainable competitive advantage.

In this paper, using the lens of the resource-based view of the firm (Wernerfelt, 1984; Barney, 1991) and the more recent dynamic capabilities approach (Teece, 2007, Teece, 2015), intangible assets are considered as an array of heterogeneous assets driving the firm's competitive advantage, i.e., enabling the firm to embark in the different activities that constitute the innovation process at the firm level. A few papers about intangibles have adopted this perspective so far (e.g., Molloy et al., 2011; Arrighetti et al., 2014; Montessor and Vezzani, 2016). In addition, using data from a large-scale business survey, i.e., the Globalinto Business Survey (Caloghirou et al., 2024), we put forward some research hypotheses about the innovation impact of different aspects of investments in intangible assets and empirically test them using a sample of 1796 firms active in a broad set of industries in manufacturing and services, across seven European countries (Germany, France, UK, Greece, Finland, Denmark, Slovenia). In particular, we explore two characteristics of a firm's decision to invest in intangibles from a strategic perspective focusing on the resources dedicated to technological and non-technological investment and further distinguishing them into internally developed (with own resources) and externally acquired intangibles.

Our results indicate that investments in both technological and non-technological intangibles play an important role in firms' innovation propensity (i.e., the introduction of product and business process innovations). Moreover, greater investments in both intangibles positively relate to achieving higher innovative turnover. Although technological intangibles exhibit a stronger relationship with product innovation and non-technological intangibles with business process innovation, our results suggest

that both intangible types are significant for innovation. Technological intangibles are critical for advancing and improving technologies that drive product innovation but also provide tools, capabilities, and data-driven insights to enhance efficiency and automation in business processes. On the other hand, non-technological intangibles can be instrumental in aligning product development with customer preferences and needs but may also contribute to process innovation through change management, organization culture, and constant improvement of practices. In this vein, our results suggest that an appropriate integration and balance of investments in a broader spectrum of intangible assets, i.e., R&D, software & databases, design, training, reputation & branding, and OBP improvement can be key to successful product and business process innovation.

Furthermore, internally developed intangibles are essential for a firm's propensity to introduce both product and business process innovation. As intangible assets often represent the firm's core competencies, their internal development and control provide significant value in innovation intensity and durable competitive advantage (Barney, 1991; Teece, 2015). On the other hand, externally acquired intangibles seem equally important for innovative turnover. This is because the economic exploitation of product innovation is based not only on the firm's internal competencies but also requires external knowledge to enhance innovation marketability. In this regard, internal intangible investments may enable firms to build critical organizational capabilities to develop innovations of increased market potential and business value and to effectively acquire intangibles from external providers.

Several policy implications arise from our analysis. First, considering the importance of both technological and non-technological intangible assets for innovation performance, policy interventions should favor the development of multiple business intangibles and not be directed towards individual intangible components (e.g., solely R&D) (Lampel et al., 2022). Therefore, a combination of well-targeted policy support instruments per intangible asset should be designed and implemented, including direct (grants, subsidies, government loans) or indirect (tax incentives) measures, appropriate reformations of the regulatory framework (e.g., product and labor market regulations, intellectual property rights systems) and improvement of financing mechanisms (e.g., banks, venture capitals, crowdfunding). The mix of measures should also be contingent upon firms' basic characteristics (size, age, sector) and their heterogeneity in strategic objectives and priorities, ensuring a more effective allocation of resources for different innovation processes (Álvarez and Crespi, 2015; Lampel et al., 2022; OECD, 2021; Thum-Thysen et al., 2017).

Second, policy measures should balance promoting intangibles' internal development and providing opportunities for utilizing intangibles developed in other firms or external entities. On the one hand, policymakers should emphasize the augmentation of internal intangible assets critical for nurturing enterprise innovation performance. Since intangible activities are human-capital intensive (Thum-Thysen et al., 2017), financial support (especially to SMEs) for acquiring, retaining, and strengthening - through training and reskilling programs - such human capital is essential. In addition, new ventures and generally micro/small firms should be supported in developing their entrepreneurial and managerial capabilities through personalized coaching and training activities as well as recruiting managers with

requisite skills (Lampel et al., 2022). On the other hand, access to complementary external intangibles, opportunities for collaboration with academic and research entities, and networking and synergies with other firms should also be facilitated. In this vein, relevant policy tools and mechanisms should be strengthened, such as promoting research collaborations between public research institutes, universities, and the private sector, as well as technology transfer offices, competence centers, intermediary institutions, and technology platforms (Kramer et al., 2011; Lampel et al., 2022; OECD, 2021; Thum-Thysen et al., 2017).

Last but not least, the impact of the various intangibles dimensions/aspects (tech and non-tech, internal and external) on innovation performance calls for appropriate common guidelines-standards for capturing sufficiently all types of intangibles in the national accounting systems and, more importantly, in the financial accounts of firms (Lampel et al., 2022; Thum-Thysen et al., 2017). Therefore, particular emphasis should be placed on addressing the underestimation of in-house developed and non-technological intangibles (Montessoro et al., 2014).

To sum up, this work can offer useful insights into the innovation studies literature and practice and the ongoing debate about intangibles investments' nature and explanatory value on innovation performance. Our study makes three contributions. First, it integrates the Knowledge Production Function idea (or extends the standard KPF approach to intangibles) with some more profound theoretical propositions about intangibles stemming from the resource-based view of the firm to reconcile productivity and innovation analysis. Second, it uses rich survey data on intangibles, allowing us to focus on a broad array of them and simultaneously explore some essential characteristics of the relevant investments. Combining these two originality elements, we offer a more comprehensive picture of the intangibles' complex role and impact on firms' innovation performance. Third, we provide interesting policy implications for adopting an enlarged understanding of intangible assets, further facilitating their creation and development at the firm level.

References

- Álvarez, R., & Crespi, G. A. (2015). Heterogeneous effects of financial constraints on innovation: Evidence from Chile. *Science and Public Policy*, 42(5), 711-724.
- Arrighetti, A., Landini, F., & Lasagni, A. (2014). Intangible assets and firm heterogeneity: Evidence from Italy. *Research Policy*, 43(1), 202-213.
- Arundel, A., & Smith, K. (2013). History of the community innovation survey. In Gault, F. (ed). *Handbook of innovation indicators and measurement*, Edward Elgar Publishing, pp. 60-87.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Caloghirou, Y., Protogerou, A., Panagiotopoulos, P. and Bavdaž M. (2024). Intangible assets investments in Europe: Findings from the Global into large-scale business survey. In C. Bloch, A. Protogerou and N. Vonortas (eds) *Intangible Assets, Productivity and Economic Growth: Micro, Meso and Macro Perspectives*, Routledge.
- Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press.

Ciriaci, D. (2017). Intangible resources: the relevance of training for European firms' innovative performance. *Economia Politica*, 34(1), 31-54.

Freeman, C. (1988). Japan: A New National System of Innovation? in Dosi, G. et al., *Technical Change and Economic Theory*, London, Pinter Publishers, pp.330-348.

Garcia, A. (2011). The relevance of marketing in the success of innovations (No. 09/2011). IPTS Working Papers on Corporate R&D and Innovation.

Griliches, Z. (1998). Issues in assessing the contribution of research and development to productivity growth. In *R&D and productivity: The econometric evidence*, pp.17-45. University of Chicago Press.

Hall, B. H., Lotti, F., & Mairesse, J. (2013). Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology*, 22(3), 300-328.

Haskel, J., & Westlake, S. (2018). Capitalism without capital. In *Capitalism without Capital*. Princeton University Press.

Kramer, J. P., Marinelli, E., Iammarino, S., & Diez, J. R. (2011). Intangible assets as drivers of innovation: Empirical evidence on multinational enterprises in German and UK regional systems of innovation. *Technovation*, 31(9), 447-458.

Lampel J., Edler J., & Gadepalli S.D. (2022). Deliverable 7.7: Grasping the impalpable: Critical appraisal of the role of public policy for intangibles, WP7: Intangible assets in the public sector and policy. GLOBALINTO: Capturing the value of intangible assets in micro data to promote the EU's Growth and Competitiveness, An Horizon 2020 project (2019-2022).

Lundvall, B-A. (1992). *National Innovation Systems: Towards a Theory of Innovation and Interactive Learning*, London, Pinter Publishers.

Martin, J., & Baybutt, C. (2021). The F words: why surveying businesses about intangibles is so hard. IARIW-ESCoE Conference, November 11-12.

Molloy, J. C., Chadwick, C., Ployhart, R. E., & Golden, S. J. (2011). Making intangibles "tangible" in tests of resource-based theory: A multidisciplinary construct validation approach. *Journal of Management*, 37(5), 1496-1518.

Montresor, S., & Vezzani, A. (2016). Intangible investments and innovation propensity: Evidence from the Innobarometer 2013. *Industry and Innovation*, 23(4), 331-352.

Montresor, S., & Vezzani, A. (2022). Financial constraints to investing in intangibles: Do innovative and non-innovative firms differ?. *The Journal of Technology Transfer*, 47(1), 1-32.

Nelson, R.R., & Rosenberg, N. (1993). Technical innovation and national systems. In: Nelson, R. R. (ed) *National Innovation Systems: A Comparative Analysis*. Oxford: Oxford University Press.

OECD (2021). Bridging the gap in the financing of intangibles to support productivity: Background paper. OECD Publishing, Paris.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and micro-foundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350.

Teece, D. J. (2015). Intangible assets and a theory of heterogeneous firms. In: Bounfour, A., Miyagawa, T. (eds), *Intangibles, Market Failure and Innovation Per-*

formance (pp. 217-239). Springer, Cham.

Thum-Thysen, A., Voigt, P., Maier, C., Bilbao-Osorio, B., & Ognyanova, D. (2017). Unlocking Investment in Intangible Assets in Europe. Quarterly Report on the Euro Area (QREA), Directorate General Economic and Financial Affairs (DG ECFIN), European Commission, vol. 16(1), pages 23-35, March.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal*, 5(2), 171-180.

Zambon, S, & Monciardini, D. (2015). Intellectual capital and innovation. A guideline for future research. *Innovation Economics and Management*, 17(2), 13-26.

DEVELOPING COMPASSIONATE WORKPLACES IN EUROPE FOR THE DIGITAL AND GREEN WORK ENVIRONMENT TO PROTECT EMPLOYEES' MENTAL AND PHYSICAL HEALTH AND WELL-BEING

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Keywords: Compassionate workplaces, wellbeing, digitization, intervention, mixed methods.

Abstract

Europe's population with serious illnesses and palliative care needs is expected to continue to grow, affecting the active working population either as patients, caregivers or bereaved persons (Wilson et al, 2021). Serious illness, caregiving tasks, dying, loss and grief spills over from employees' personal lives to the workplace. We refer to these events as end-of-life (EOL) experiences. The EU-CoWork¹ project aims 1) to explore and understand the influence of changing workplace organization due to digitization on wellbeing, performance, job quality, and work culture for employees confronted with serious illness, family caregiving, death, dying and loss and their colleagues, and 2) to develop and evaluate tailored Compassionate Workplace Programs (CWPs) as health promotion strategies to maintain and support employee health and well-being in the work environment across different national and labor contexts in Europe.

The digitization of the work environment occurs at a fast pace and influences various psychosocial factors of work. The use of Information and Communication Technology (ICT) affects both positively and negatively the psychosocial work environment, which impacts employee mental and physical health and wellbeing (Bodner et al, 2022). Telework and ICT-mobile work have been reported to improve work-life balance, help employees juggle child-care, improve autonomy regarding working time, lead to higher productivity, increase motivation, reduce absenteeism and turnover, and reduce commuting time (Eurofound, 2022). However, telework and digital management tools (such as performance monitoring and digital HR management) also have been found to lead to longer working hours, work-home interference, work intensification, greater ergonomic risks, social isolation and poor relationships with co-workers and supervisors (El Kadri Filho & Lucca, 2022). It results in indirect communication between management and employees, making management tasks and supporting employees more difficult. Technological surveillance has even been reported to increase formal management control and thus reduce employees' feelings of autonomy (Nastjuk et al, 2023). Digitization has influenced the work environment and job demands and resources such that employees can feel less or not supported when coping with EoL experiences, e.g. hybrid work increases schedule control and autonomy which might facilitate caregiving, but may also impede

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contact with colleagues and social support from co-workers, and as such may lead to social isolation and lower organizational commitment. CWP's aim to facilitate a work environment that projects and improves the mental and physical health and wellbeing of employees.

A consortium of five established research teams (VUB, LTU, UG, USFD and AUEB) and three workplace advocacy and policy groups (IDEWE, HSE, and Sorgenetz) across five countries (Belgium, Sweden, Austria, the UK and Greece) brings together expertise in healthcare science, nursing, labor sociology, work and organizational psychology, human resources management and palliative and EoL care. The core of this project is a 4-country cross-national mixed-methods intervention study with an embedded process and impact evaluation. The EU-CoWork project started in January 2024. Tailored CWP's are in the process of been developed in 12 European workplaces. Baseline measurements (pre-intervention test) inform the facilitated co-creation process of the tailored Compassionate Workplaces programs. Data will be collected in at least three points in time and the longitudinal and cost-effectiveness analyses will evaluate the effects of the EU-CoWork intervention on employees' mental and physical health and well-being, as well as managers' capabilities in reducing healthcare costs, improving employee performance and fostering a healthier, more supportive work culture.

In Greece four workplaces have been recruited. At the initial phase of our collaboration with the companies we are collecting qualitative data through a) company documents and policies (document analyses) b) interviews with members of the top management team, the HR manager, and employees of the company, and c) focus group with a core development group that has been created. To understand the organizational context we have started to develop a needs and assets mapping within each company. The next step is to conduct a quantitative analysis through the questionnaire we have developed as a Consortium. At the Research Colloquium at Syros we will present the preliminary findings of our work in Greek companies.

References

Bodner, A., Ruhl, L., Barr, E., Shridhar, A., Skakoon-Sparling, S., and Card, K. G. (2022). "The impact of working from home on mental health: a cross-sectional study of Canadian worker's mental health during the third wave of the covid-19 pandemic". *International Journal of Environmental Research and Public Health*, 19(18), 11588.

El Kadri Filho, F., and de Lucca, S. R. (2022). "Telework conditions, ergonomic and psychosocial risks, and musculoskeletal problems in the COVID-19 pandemic". *Journal of Occupational and Environmental Medicine*, 64(12), e811-e817.

Eurofound (2022). The rise of telework: Impact on working conditions and regulations, <https://www.eurofound.europa.eu/publications/report/2022/the-rise-in-telework-impact-on-working-conditions-and-regulations>.

Nastjuk, I., Trang, S., Grummeck-Braamt, J. V., Adam, M. T., & Tarafdar, M. (2024). "Integrating and synthesising technostress research: a meta-analysis on technostress creators, outcomes, and IS usage contexts". *European Journal of Information Systems*, 33(3), 361-382.

Wilson, D. M., Punjani, S., Song, Q., and Low, G. (2021). A study to understand the impact of bereavement grief on the workplace. *OMEGA-Journal of Death and*

Dying, 83(2), 187-197.

MODAPTO AND RECONFIGURABLE MANUFACTURING: ENABLING MODULAR INTELLIGENCE THROUGH DIGITAL TWINS AND ROBOTIC OPTIMIZATION

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Keywords: MODAPTO, industrial systems, modular design, optimization.

MODAPTO Project Overview

MODAPTO is a European research project that aims to realize the vision of highly flexible industrial systems through modular design and distributed intelligence enabled by interoperable Digital Twins (DTs). By promoting reconfigurability at the factory floor level and beyond, MODAPTO supports smarter module and production line design, efficient reconfiguration, and intelligent decision support. Its DTs are built upon industrial standards to ensure easy adoption and interoperability. MODAPTO will be deployed across three industrial use cases involving four manufacturers, each operating at different levels of complexity, to demonstrate improvements in key performance indicators such as efficiency, cost, quality, energy use, and sustainability. The project also fosters widespread adoption through training activities, business model development, and active engagement with both large manufacturers and SMEs. Central to MODAPTO's impact is its open-source, standard-compliant framework and toolkit, which enable predictive maintenance, simulation, and optimization across modular production systems—facilitating collective intelligence among distributed DTs and ensuring transferability to a wide range of industrial sectors.

Our Contribution within MODAPTO: RMS and Robotic Optimization

In the context of MODAPTO, our research focuses on developing a Reconfigurable Manufacturing System (RMS) architecture that integrates Digital Twins and smart optimization services for robotic pick-and-place operations. By aligning with MODAPTO's modular and interoperable philosophy, we propose a flexible system that enables real-time monitoring, distributed decision-making, and adaptive reconfiguration of robotic tasks in kitting operations. Our architecture leverages a simulation service that not only optimizes pick-and-place sequences through exact and heuristic methods but also evaluates alternative Gravity Rack (GR) configurations to further reduce cycle times. The approach models the problem as a Bipartite Traveling Salesman Problem (BTSP), and our results show that combining layout optimization with sequence planning can reduce operational time by up to 30%. This work contributes directly to MODAPTO's objectives by enhancing modular intelligence, supporting rapid changeovers, and laying the groundwork for scalable, data-driven manufacturing supported by collective intelligence among production modules.

This research work has been conducted within the framework of the MODAPTO project (MODULAR MANUFACTURING AND DISTRIBUTED CONTROL VIA

INTEROPERABLE DIGITAL TWINS), which has received funding from the European Union's Horizon Europe research and innovation program under grant agreement No 101091996.



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