# Artificial Intelligence (AI) and Organisation: Strategies for Implementation of AI in Organisations

by

**Shayan Rashidi**

**Submitted in fulfilment of the requirements for the degree of**

**Doctor of Philosophy (PhD)**

**In Management**

**(Entrepreneurship and Strategy)**

**Department of Entrepreneurship and Strategy**

**Lancaster University Management School**

**Declaration**

I, Shayan Rashidi, hereby declare that this PhD thesis, entitled, "*Artificial Intelligence (AI) and Organisation: Strategies for Implementation of AI in Organisations*", is my own developed work and has not been submitted in the same form elsewhere (unless where unless where relevant to fulfil the requirements of the PhD degree).

This thesis by alternative format (papers) has been framed within the postgraduate research regulations for the award of the Doctor of Philosophy (PhD) in Entrepreneurship and Strategy and under the guidance of Prof. Olufunmilola (Lola) Dada and Dr Richard Williams in the Department of Entrepreneurship and Strategy, Lancaster University Management School, UK.

Shayan Rashidi
July 2025

To my lovely mother, father, and beautiful wife, and to all my dear family members whose support made this journey possible.

## Acknowledgements

Pursuing a full-time PhD, particularly as an international student travelling abroad for the first time, was very challenging for me. Despite all the challenges associated with this journey, it was an impressive experience that equipped me with everything I may need not only for pursuing a career in academia, but also for the rest of my life. Lancaster was a wonderful place to be as a postgraduate researcher, and I am deeply pleased and grateful for having had this opportunity to complete my education here.

There are a number of people I need to thank for their constant support and encouragement, which made this possible. First and foremost, I want to express my warmest thanks to my supervisors, Professor Olufunmilola (Lola) Dada and Dr Richard Williams, for their significant support since I started my PhD. I truly believe that without their support and guidance, completion of my PhD would not have been feasible, and I am very grateful for their contribution.

I should also thank Professor Mark Freel, Dr Marian Iszatt-White, and Dr Robert Demir, who educated me in the theoretical and methodological concepts that I utilised throughout my PhD studies.

I also tremendously thank my parents, Afsaneh and Mohammadreze, who did everything they could to support me over these years, and my wonderful wife, Sana, who has helped me throughout this journey, particularly during the period when we were far apart. Finally, I thank all my family members—my loving grandmothers and uncles—who all supported me through these years.

**Abstract**

Artificial Intelligence (AI) offers a promising technology with significant transformative power to reshape organisations. The influential role of technology in organisational contexts is not a novel concept. However, due to AI's ability to automate tasks traditionally performed only by humans and function as a novel kind of intelligence alongside human experts, further investigation into AI's organisational aspects is needed. In this context, this study advances the organisational studies of AI through three related papers. The systematic literature review paper examines how Digital Transformation (DT) is enabled by AI. Instead of solely focusing on technological aspects of AI, this paper reveals that a combination of technological, organisational, and environmental factors, alongside particular strategies, plays a crucial role for AI-enabled DT. The second research paper, studying knowledge-intensive start-ups, challenges the traditional Knowledge-Based View (KBV) of the firm. It demonstrates how AI can collaborate with Human Intelligence (HI) in the creation and utilisation of both tacit and explicit knowledge. The third paper focuses on higher education settings and adopts an ecosystem perspective to illustrate how Generative AI (Gen AI) functions as a novel intelligent agent by augmenting certain knowledge activities that have traditionally been carried out by HI. Beyond theoretical contributions, the research provides actionable insights for managing AI-based DT and orchestrating the collaboration between AI and HI in the form of augmented intelligence. These insights offer timely guidance for knowledge-intensive organisations to navigate the opportunities and challenges associated with AI adoption, whilst simultaneously gaining and sustaining competitive advantages through innovation.

## Table of Contents

**List of Tables**



**List of Figures**

# Chapter 1: Introduction

Technological innovations and their associated advantages have caused a substantial transformation in the economy over the past few decades (Demirkan et al., 2016). However, such a significant impact is not novel. Throughout history, the emergence of cutting-edge breakthroughs, such as the invention of the steam engine, the widespread accessibility of electricity, and the introduction of World Wide Web (WWW), have reshaped how organisations and businesses operate, and today Artificial Intelligence (AI) as a technology capable of performing human-like behaviour, plays the same critical role in this ongoing transformation (Xie and Wang, 2020; Ransbotham et al., 2017; Haenlein and Kaplan, 2019; Brynjolfsson and McAfee, 2017). Since AI was introduced as a concept during the Dartmouth Conference in 1956, it has evolved to the current widespread adoption of sophisticated Large Language Models (LLMs) in designing and developing Generative AI (Gen AI). Throughout this evolution, the primary focus of AI has been on behaving as intelligent as humans through training on extensive datasets (Haenlein and Kaplan, 2019; Goodfellow et al., 2016). In other words, AI can be defined as a technological concept comprising sophisticated learning algorithms that can perform a wide range of tasks in a more efficient and much quicker way compared to human performance (Baird and Maruping, 2021; Jordan and Mitchell, 2015).

## 1.1 Background to the study

Recent technological advancements, particularly in storing significant quantities of data and computational processing capacities, alongside easy access to sophisticated generative models, have created an environment where organisations and businesses have unprecedented opportunities to incorporate AI and the benefits associated with it (Modgil et al., 2025; Baabdullah, 2024; Uren and Edwards, 2023). However, benefiting from a cutting-edge technology like AI is not all about the technology itself. For example, the adoption of emerging technologies does not necessarily enable their adopters to realise the advantages that these technologies offer (Bharadwaj, 2000). This implies that, beyond the technological aspects of AI, its successful adoption by organisations is associated with a range of crucial organisational considerations. In this context, Digital Transformation (DT), as an organisational concept whose primary focus is on emerging technologies and the resulting innovated value creation pathways enabled by these technologies within organisations, can explain how cutting-edge technologies like AI can provide advantages to their adopters (Naimi-Sadigh et al., 2022; Vial, 2019; Hess et al., 2016).

As mentioned earlier, DT is focused on the integration of emerging technologies into organisations and the utilisation of these technologies to innovate the value-creation pathways followed by these organisations. In this context, depending on how organisations and their value-creation pathways are viewed, different innovation practices for altering these value-creation pathways can be considered. Drawing on the Knowledge-based View of the firm (KBV), organisations are viewed as entities whose core asset is knowledge and their primary focus for value creation is on the creation and utilisation of knowledge (Schulz, 2001; Sveiby, 2001; Grant, 1996; Grant and Baden-Fuller, 1995). From this perspective, innovation practices occur when AI is introduced into the knowledge creation and knowledge utilisation processes of organisations as the main activities that underlie the organisations' value creation processes.

According to the KBV perspective, the creation and utilisation of knowledge are only carried out by the agency of humans (Grant, 1996). This means that humans, as the only intelligent agents within the organisations, are the sole intelligent players with a crucial role in the creation and utilisation of knowledge. In this context, when AI is the cutting-edge technology adopted by knowledge-intensive organisations, the resulting innovation can be much more disruptive since these processes incorporate AI not only as a tool that can serve Human Intelligence (HI) but also as a novel kind of non-human intelligent agent that can collaborate with HI. In this context, this thesis advances the organisational studies of AI through three interconnected research papers. First, a systematic literature review paper examines AI-based DT. This paper, by synthesising empirical research papers focused on how to manage AI within the DT process, proposes a conceptual model that highlights enabler factors required for the utilisation of AI within DT, strategies that organisations should adopt to be transformed digitally based on AI competencies, and potential outcomes of AI-based DT. Next, the second research paper, by gathering empirical evidence from knowledge-intensive start-ups, studies how the collaboration between AI and Human Intelligence (HI) in the form of augmented intelligence can be managed within the innovation practices of knowledge-intensive start-ups. Finally, the third research paper by, studying Lancaster University Management School (LUMS), in the U.K. as a representative case for knowledge-based institutions, examines the impact of Gen AI on the value propositions offered by LUMS from an ecosystem perspective. This research aims to establish a strong position within the scholarly discourse on organisational aspects of AI, particularly from the KBV and ecosystem perspectives. To the best of my knowledge, this is the first research that depicts an active collaborative and participatory role for AI within knowledge creation and utilisation activities, which have traditionally been dominated solely by HI.

The first paper, the Systematic Literature Review (SLR), starts with studying AI-enabled DT. Among different cutting-edge technologies that can enable DT, AI appears more promising as it requires considerably fewer programming efforts compared to traditional information systems while simultaneously offering performance that scales with access to extensive data repositories and sophisticated computational algorithms, which are more accessible now than at any time in history (Grønsund and Aanestad, 2020; Brynjolfsson and McAfee, 2017). Due to these distinguishable characteristics of AI, alongside recent advancements in generative models' performance in producing human-like content, DT enabled by AI is potentially associated with significant advantages that can result in altered value creation pathways followed by organisations, and ultimately lead to gaining and sustaining competitive advantages.

Despite the great merits associated with AI, its implementation within the organisational context is not necessarily straightforward. This shows the necessity of having clear approaches and structures for successful AI-enabled DT (Verhoef et al., 2021). In this regard, a wide range of empirical studies has been conducted to examine AI-based DT. However, these studies and their empirical findings are highly fragmented, and there has been no synthesis of these empirical insights to propose systematic knowledge on AI-based DT. To address this gap, this study will address, within the SLR in Chapter 2, the following research question:

RQ: How can AI be managed within the DT process of organisations?

The first research paper contributes to the extant literature on AI-based DT in different ways. First, by identifying positive outcomes associated with AI-based DT, this research found that specific theoretical perspectives like the resource-based view of the firm (RBV), knowledge-based view of the firm (KBV), and dynamic capabilities were among the most adopted theoretical lenses across the studies whose findings provided insights on positive outcomes of AI-based DT. The particular focus of these theories on how organisations can gain competitive advantages implies that appropriate utilisation of AI within the DT process can be considered as one of the main resources for gaining competitive advantages. Second, this research introduces three specific strategies that can be followed by organisations for their AI-based DT. Introducing different layers of strategies for AI-based DT with varying degrees of complexity for each strategy, it was shown that organisations can start their AI-based DT with the automation approach and then continue through more complicated approaches (i.e. augmentation and co-creation). Third, by introducing a wide range of organisational and environmental enablers alongside technological ones, this study demonstrates that AI-based DT is a multi-faceted organisational phenomenon rather than a merely technological concept.

Regarding the second paper, according to the findings from the SLR paper that introduced augmentation as one of the strategies for incorporating AI, this research paper examines augmented intelligence in the context of knowledge-intensive start-ups. Drawing on the KBV perspective, organisations are entities whose crucial resource for value creation is knowledge and their primary operation is focused on creation and/or utilisation of knowledge. (Schulz, 2001; Sveiby, 2001; Grant, 1996; Grant and Baden-Fuller, 1995). In such a context, innovation can happen through the creation of novel knowledge, either from scratch or by integrating knowledge from different sources (i.e., internal and external knowledge), or by utilising knowledge in a novel way (Cohen and Levinthal, 1990; Nonaka and Takeuchi, 1995; Grant, 1996; Eisenhardt et al., 2000; Muñoz-Bullón et al., 2020a; Muñoz-Bullón et al., 2020b). From this perspective and in the context of the knowledge-intensive sector, where HI has traditionally played the major role in the creation and utilisation of knowledge, the augmentation strategy that focuses on collaboration between AI and HI is highly relevant. The incorporation of AI by knowledge-intensive start-ups is shaping innovation practices where AI and HI, in the form of augmented intelligence, collaborate within the knowledge creation and knowledge utilisation activities. In this regard, this study examines five knowledge-intensive start-ups to answer the following research question:

RQ: How can augmented intelligence be managed in the innovation practices of knowledge-based firms?

The second research paper, adopting a KBV perspective, focused on how augmented intelligence can be managed across the innovation practices of knowledge-intensive start-ups. Its findings make a significant contribution to the extant literature on both KBV and augmented intelligence. By introducing different collaborative settings between AI and HI within the knowledge creation and knowledge utilisation activities, this research demonstrates the specific roles that each can play within these processes. This proposed task division between AI and HI in the creation and utilisation of knowledge (i.e. explicit and tacit knowledge) challenges the existing conceptualisation of these activities in the realm of KBV, as this is the first time to the best of my knowledge, that non-human intelligence is introduced into these processes.

The third research paper studies Gen AI in the context of knowledge-based institutions. Drawing on the ecosystem-as-structure perspective introduced by Adner (2017) and selecting Lancaster University Management School (U.K.) as a representative case for knowledge-based institutions, this study examines how Gen AI can affect the value propositions of LUMS' ecosystem. Recent advancements in LLMs have caused the emergence of a group of AI models, called Gen AI, which are capable of generating human-like content (Roumeliotis and Tselikas, 2023; Stokel-Walker, 2023). The flexibility of these generative models in producing human-like outputs across a wide range of areas, alongside their capability to adjust their outputs according to the inputs provided by users, has made these models efficient and popular across different fields (Susnjak and McIntosh, 2024). In this context, universities as knowledge-based institutions whose primary activities are the creation and dissemination of knowledge (Adeinat and Abdulfatah, 2019; Bano and Taylor, 2015; Rowley, 2000) represent a suitable context for embracing Gen AI (Kulkarni et al., 2024; Kung et al., 2023). However, despite the great opportunities associated with Gen AI in the higher education context, alongside the potential adverse impacts that Gen AI can cause in this context, this field suffers from a lack of well-crafted empirical studies. In this regard, the third research paper of this thesis aims to fill this significant gap by addressing the following research question:

RQ: How can Gen AI affect the proposed value of a knowledge-based institution's ecosystem?

Findings from the third research paper make two novel contributions to the literature on Gen AI in higher education and ecosystem perspective. First, the study highlights that Gen AI, by augmenting academicians in their main activities (i.e. knowledge creation and knowledge dissemination), influences the value propositions offered by higher education service providers. This finding implies that rather than replacing human workforces (i.e. academic staff), the integration of Gen AI into the higher education sector results in augmenting these human experts. Second, by introducing Gen AI as a player that actively participates in the underlying activities for creating the value propositions offered by the higher education ecosystem, this study introduces the first known, non-human ecosystem player. Although viewing technology as a crucial component of the ecosystem is not necessarily a novel phenomenon, introducing Gen AI as a technology-enabled player actively involved in the main activities of the higher education ecosystem through collaboration with other players is a novel contribution to the literature on Gen AI in higher education and ecosystem perspective.

## 1.2. Motivation of this study

While in recent years AI has experienced remarkable progress, there is a critical gap in recognising its organisational aspects, particularly when it functions as a novel form of non-human intelligence capable of collaborating with HI, rather than a mere automation tool. Traditional theories from the organisation studies literature, including the Knowledge-Based View (KBV) of the firm and ecosystem perspectives, have been developed based on an assumption that argues humans are the sole organisational intelligent agents. Drawing on this view, when these theories conceptualise knowledge creation, knowledge utilisation, and value creation activities, they implicitly assume that human agency is the only contributor to these processes. However, the emergence of AI, particularly with its capacity to participate actively and independently in cognitive tasks, and to generate human-like content, fundamentally challenges this assumption. In other words, existing theoretical lenses from organisation and management studies have inherent limitations in fully capturing the complexity of the contemporary AI age.

This thesis is motivated by the strong need to reconceptualise how AI can be leveraged by organisations, particularly across the sectors where intelligence, expertise, and knowledge have traditionally been the exclusive domain of humans. In other words, this thesis examines the organisational aspects of AI, specifically when AI is viewed as an intelligent collaborator, through investigating three interconnected dimensions of this phenomenon: how AI can enable organisational transformation through DT processes; how AI and HI can collaborate as augmented intelligence in the innovation practices of knowledge-intensive start-ups; and how Gen AI as a novel ecosystem actor can affect value propositions offered by higher education institutions.

The core focus of this thesis is understanding how AI, as a form of non-human intelligence, functions in organisational contexts that have traditionally been the exclusive domain of human intelligence, rather than prescriptive implementation strategies. This focus is deliberately centred on knowledge-intensive contexts as these settings represent an appropriate environment where AI functionality and role can be investigated in a more comprehensive sense rather than as mere automation. By examining AI through the lens of DT, KBV, and ecosystem perspectives, this thesis advances scholarly and practical understandings of organisational aspects of AI beyond conventional automation narratives. In this regard, this thesis provides a rigorous response to the critical gap that exists in the literature, which has largely overlooked the theoretical and practical implications of introducing non-human intelligence into processes that have historically depended solely on human intelligence.

### 1.3. Contributions of the thesis

AI is a promising technology with extensive potential to provide organisations with significant benefits. Despite the great recent technical progress in this field, its organisational aspects have been less explored. This implies that although AI is believed to have influential power to transform organisations, there have been scarce insights on how organisations can take advantage of this technology. The current thesis advances the discourse on organisational aspects of AI by making a number of major contributions as discussed below.

First, this thesis, by focusing on AI-DT, reveals how AI can enable organisational transformation. Going beyond common technological aspects usually considered as the main requirements for integrating AI into organisations, this study offers a more holistic and comprehensive picture of AI-based DT. It does so by identifying essential organisational enablers and environmental factors that influence the transformation process. This is a crucial contribution to the current literature on AI and organisational studies as it demonstrates the critical non-technological resources required for DT enabled by AI. Alongside identifying essential enablers that affect AI-based DT, this thesis offers clear approaches through which AI-based DT can be carried out by introducing distinct strategies for using AI within the DT process (i.e. automation, augmentation, and co-creation), the corresponding positive outcomes associated with each of these strategies (i.e. enhanced efficiency and enhanced performance, informed decision making, and business model innovation), and the generic negative outcomes linked with these strategies (i.e. job-related issues, privacy issues, and ethical issues). These findings collectively demonstrate how AI-based DT can be managed, with particular focus on the required resources for this process, strategies to implement it, and the consequences associated with this process.

Second, drawing on the KBV theory, this thesis reveals how augmented intelligence can be managed across the innovation practices of knowledge-intensive start-ups. These insights make a significant contribution to the KBV theory. According to the KBV perspective, knowledge, in either explicit or tacit form, is organisations' most crucial resource, and knowledge creation and utilisation constitute the primary activities of organisations whose core resource is knowledge. In the realm of KBV theory, while the creation and utilisation of explicit knowledge can be carried out by the incorporation of non-human intelligence, tacit knowledge is a type of knowledge whose creation and utilisation are only limited to human agency. In this context, the current thesis challenges the long-standing discourse that non-human intelligence has no contribution to the creation and utilisation of tacit knowledge, by offering innovation practices comprising augmented intelligence and proposing a division of tasks between AI and HI for each innovation practice. Findings from this thesis demonstrate that not only can AI participate in the creation and utilisation of explicit knowledge, but it can also contribute to the creation and utilisation of tacit knowledge by empowering HI in its knowledge-related activities (i.e. knowledge creation and knowledge utilisation). This argument is a novel and significant contribution towards the KBV theory since this is the first known time that an active role of non-human intelligence, AI, is recognised within knowledge creation and knowledge utilisation activities.

Third, from an ecosystem perspective, this thesis introduces AI as a new independent player within the higher education ecosystem. Viewing technologies as crucial ecosystem constituents is not necessarily a novel concept. However, this study makes a novel contribution to ecosystem literature by conceptualizing AI as a non-human intelligent agent that actively collaborates with other players in the higher education ecosystem to create value. This thesis, by focusing on one higher education service provider as a representative case of knowledge-based institutions, reveals how Gen AI can affect the value propositions offered by these types of institutions' ecosystems. This study demonstrates that Gen AI, by taking a distinct role as an ecosystem player, is important for knowledge creation and knowledge dissemination activities alongside human experts.

### 1.4. Structure of the thesis

The rest of this thesis is structured as follows: first, the SLR paper on AI-based DT is presented in Chapter 2. This is followed by a qualitative paper studying the management of augmented intelligence in innovation practices of knowledge-intensive start-ups in Chapter 3, and additionally, another qualitative research paper exploring how Gen AI can affect the value propositions offered by knowledge-based institutions' ecosystem in Chapter 4. Both of these empirical papers are particularly focused on studying the augmentation role of AI as a kind of non-human intelligence capable of collaborating with HI. Next, within the discussion section in Chapter 5, theoretical and practical implications are discussed. Finally, Chapter 6 presents the conclusion of this thesis.

## References


Adeinat, I. M., & Abdulfatah, F. H. (2019) Organizational culture and knowledge management processes: case study in a public university. *VINE Journal of Information and Knowledge Management Systems*, 49(1), 35-53.

Adner, R. (2017) Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, 43(1), 39-58.

Baabdullah, A. M. (2024) The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. *International Journal of Information Management*, 75, 102745.

Baird, A., & Maruping, L. M. (2021) The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS Quarterly*, 45(1), 315-341.

Bano, S., & Taylor, J. (2015) Universities and the knowledge-based economy: perceptions from a developing country. *Higher Education Research & Development*, 34(2), 242-255

Bharadwaj, A. S. (2000) A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. *MIS Quarterly*, 24(1), 169-196.

Brynjolfsson, E., & McAfee, A. (2017) The business of artificial intelligence. *Harvard Business Review*, 7(1), 1-2.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1), 128–152.

Demirkan, H., Spohrer, J. C., & Welser, J. J. (2016) Digital innovation and strategic transformation. *IT Professional*, 18(6), 14-18.

Eisenhardt, K. M., Santos, F. M., Pettigrew, I. A., Thomas, H., & Whittington, R. (2000) Knowledge based view. *Handbook of strategy and management.* London: Sage Publications.

Goodfellow, I., Bengio, Y., & Courville, A. (2016) *Deep learning* (1st ed). Cambridge, MA: MIT Press.

Grant, R. M. (1996) Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109-122.

Grant, R. M., & Baden-Fuller, C. (1995) A knowledge-based theory of inter-firm collaboration. *Academy of Management Proceedings*, 1995(1), 17-21.

Grønsund, T., & Aanestad, M. (2020) Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems*, 29(2), 101614.

Haenlein, M., & Kaplan, A. (2019) A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016) Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, 15(2), 123-139.

Jordan, M. I., & Mitchell, T. M. (2015) Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255-260.

Kulkarni, M., Mantere, S., Vaara, E., van den Broek, E., Pachidi, S., Glaser, V. L., Gehman, J., Petriglieri, G., Lindebaum, D., Cameron, L. D., Rahman, H. A., Islam, G., & Greenwood, M. (2024) The Future of Research in an Artificial Intelligence-Driven World. *Journal of Management Inquiry*, 33(3), 207-229.

Kung, T. H., Cheatham, M., Medenilla, A., Sillos, C., De Leon, L., Elepaño, C., Madriaga, M., Aggabao, R., Diaz-Candido, G., Maningo, J., & Tseng, V. (2023) Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models. *PLOS Digital Health*, 2(2).

Modgil, S., Gupta, S., Kar, A. K., & Tuunanen, T. (2025) How could Generative AI support and add value to non-technology companies–A qualitative study. *Technovation*, 139, 103124.

Muñoz-Bullón, F., Sanchez-Bueno, M. J., & De Massis, A. (2020a). Combining Internal and External R&D: The Effects on Innovation Performance in Family and Nonfamily Firms. *Entrepreneurship Theory and Practice*, 44(5), 996–1031.

Muñoz-Bullón, F., Sanchez-Bueno, M. J., & Nordqvist, M. (2020b). Growth intentions in family-based new venture teams: The role of the nascent entrepreneur's R&D behavior. *Management Decision*, 58(6), 1190–1209.

Naimi-Sadigh, A., Asgari, T., & Rabiei, M. (2022) Digital transformation in the value chain disruption of banking services. *Journal of the Knowledge Economy*, 13(2), 1212-1242.

Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company : how Japanese companies create the dynamics of innovation. Oxford University Press

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017) Reshaping business with artificial intelligence: Closing the gap between ambition and action. *MIT Sloan Management Review*, 59(1).

Roumeliotis, K. I., & Tselikas, N. D. (2023) Chatgpt and open-ai models: A preliminary review. *Future Internet*, 15(6), 192.

Rowley, J. (2000) Is higher education ready for knowledge management?. *International Journal of Educational Management*, 14(7), 325-333.

Schulz, M. (2001) The uncertain relevance of newness: Organizational learning and knowledge flows. *Academy of Management Journal*, 44(4), 661-681.

Stokel-Walker, C. (2023) ChatGPT listed as author on research papers: Many scientists disapprove. *Nature*, 613, 620-621.

Susnjak, T., & McIntosh, T. R. (2024) Chatgpt: The end of online exam integrity?. *Education Sciences*, 14(6), 656.

Sveiby, K. E. (2001) A knowledge-based theory of the firm to guide in strategy formulation. *Journal of Intellectual Capital*, 2(4), 344-358.

Uren, V., & Edwards, J. S. (2023) Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68, 102588.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021) Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-90.

Vial, G. (2019) Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, 28(2), 1-27.

Xie, X., & Wang, H. (2020) How can open innovation ecosystem modes push product innovation forward? An fsQCA analysis. *Journal of Business Research*, 108, 29-41.

# Chapter 2: Managing artificial intelligence within the digital transformation process of organisations: A systematic review of the literature

Shayan Rashidi, Olufunmilola (Lola) Dada, and Richard Williams

Presented at British Academy of Management (BAM) Conference 2023, won the best paper award in the Organisational Transformation, Change and Development track

**Abstract**

The adoption of Artificial Intelligence (AI) by organisations for their digital transformation (DT) initiatives is a promising area with persistent challenges. There has been no comprehensive synthesis of empirical findings to identify critical factors associated with AI-based DT. Different studies from various theoretical perspectives have been conducted to study how organisations can take potential advantage of AI through their DT journeys. The current research aims to provide a systematic review of empirical studies to investigate how AI can be managed within DT. Findings from the reviewed studies were used to develop a model for managing AI-based DT. The developed model provides insights into enabling factors required for the utilisation of AI within DT, strategies that organisations should adopt to be transformed digitally based on AI competencies, and potential outcomes of AI-based DT.

Keywords: Artificial Intelligence, Digital Transformation, Systematic Literature Review, Digital Transformation Strategy.

## 2.1. Introduction

Due to recent advancements in digital technologies such as the Internet of Things (IoT), blockchain, and Artificial Intelligence (AI), Digital Transformation (DT) has attracted significant attention from both academicians and practitioners (Verhoef et al., 2021). DT has emerged as a concept that focuses on the incorporation of these digital technologies by organisations to alter and innovate their value creation pathways as a strategic response to the potential challenges that may result from these disruptive technologies, and at the same time, take any competitive advantages that they may provide (Naimi-Sadigh et al., 2022; Vial, 2019; Hess et al., 2016; Fitzgerald et al., 2014). In other words, DT is an approach to enable organisations to take proper actions in response to rapidly changing environments to sustain their competitive advantages or achieve new ones (Rêgo et al., 2021; Demirkan et al., 2016).

Despite the clear and unified function of DT, how organisations have undergone this transformation could vary depending on the type of enabler technology (Kraus et al., 2021). For this reason, organisations, as entities that are supposed to be transformed digitally, and scholars, as individuals who are interested in studying this phenomenon, should be clear about the kind of technology that should be exploited for this transformation. In this regard and among different types of emerging technologies, AI, due to its significant power to transform many aspects of organisations and societies, has been selected for the aims of the current study (Boyd and Holton, 2018). AI is an umbrella term mostly defined as a technology that focuses on sophisticated algorithms learning to perform certain tasks as intelligent as humans by exploiting extensive quantities of data (Baird and Maruping, 2021; Haenlein and Kaplan, 2019; Jordan and Mitchell, 2015). From this point of view, a range of concepts, such as machine learning and deep learning algorithms, big data analytics capabilities, and applications such as digital assistants and robots, can be considered forms of AI technology that enables organisations' DT, as all of them have the same functionality for learning intelligent behaviour to perform specific tasks by exploiting a huge volume of data. In this context, AI seems to have much more transformative power than other emerging technologies due to several factors: the considerable volumes of data generated daily, complemented by recent progress in computing power that has made exploiting these data straightforward, alongside the low dependency of AI algorithms' functionality on programming efforts compared to traditional information systems (Grønsund and Aanestad, 2020; Brynjolfsson and McAfee, 2017)

However, despite the promises and opportunities associated with AI and its application, it cannot give any advantage to organisations unless they know how and under what circumstances AI should be used for DT purposes. From this perspective, various empirical studies have been conducted to study DT based on AI competencies. However, there has not been any known comprehensive study to synthesise these empirical findings to carry out a systematic literature review to investigate how AI can be managed within the DT process. In this regard, the current study is designed to address this gap by undertaking a systematic review of empirical studies in order to address the following research question: How can AI be managed within the DT process of organisations?

In the next section, the methodology employed to conduct this study is explained. Then, findings from this review, theoretical and practical implications, limitations, possible research areas for future studies and conclusion of this review are discussed.

### 2.2. Methodology

This research utilised a systematic literature review methodology (Barroso and Laborda, 2022; Matt et al., 2022; Dada, 2021). By employing this method, the current study developed robust evidence of AI-based DT by synthesising the available contributions in this field (Hakala, 2011). This method was appropriate for the aim of this study because of the transparency that it provided for exploiting prior studies (Dada, 2018; Parris and Peachey, 2013).

#### 2.2.1 Data collection

*Inclusion criteria*. According to the study by Wang and Chugh (2014), three main inclusion criteria were identified to decide which studies should be reviewed, comprising search boundaries, search keywords, and coverage period. Regarding the search boundaries, four electronic databases were utilised namely, ScienceDirect, Scopus, Web of Science, and ABI/INFORM Complete (ProQuest). DT is a phenomenon that focuses on fundamental changes and transformation to reap digital technologies' rewards (Naimi-Sadigh et al., 2022). Therefore, to extract the most informative studies from the literature, it is essential to consider technological keywords in addition to the keywords associated with DT. In this regard, two groups of search keywords, entitled technical keywords, and business keywords, were used in this study. While the first group of keywords consisted of technical search terms that focused on AI technology, the second group comprised concepts related to DT. These keywords and how they were used to find relevant studies on the aforementioned databases are shown in the following table (Table 1). Finally, regarding the coverage period, the current study was limited to studies published up to February 2023. DT based on AI is an emerging concept whose starting year is not clear. For this reason, in terms of the coverage period, the starting year was not restricted in order to find all relevant studies in the literature and avoid missing any evidence.

Table 1. Searching procedure for the systematic literature review

| Technical search keywords | Business search keywords | Combination of Keywords | Search criteria for ScienceDirect | Search criteria for Scopus | Search criteria for Web of Science | Search criteria for ABI/INFORM Complete (ProQuest) |
|---|---|---|---|---|---|---|
| "artificial intelligence", "AI", "machine learning", "deep learning", "reinforcement learning", "neural networks", "convolutional neural networks", "recurrent neural networks", "computer vision", "image recognition", "speech recognition", "digital assistants", "virtual assistants", "intelligence | "digital transformation", "digital disruption", and "digital change" | ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural networks" OR "convolutional neural networks" OR "recurrent neural networks" OR "computer vision" OR "image recognition" OR "speech recognition" OR "digital assistants" OR "virtual assistants" OR "intelligence assistants" OR | Search mode (Boolean operators of OR/AND); search fields (title, abstract or author-specified keywords); article type (research articles); subject areas (business, management and accounting); coverage period (up to February 2023), language (English) | Search mode (Boolean operators of OR/AND); search fields (article title, abstract, keywords); document type (article); subject area (business, management and accounting); source type (journal); coverage period (up to February 2023), | Search mode (Boolean operators of OR/AND); search fields (title and abstract); document type (article); subject area (business and management); coverage period (up to February 2023), language (English) | Search mode (Boolean operators of OR/AND); search fields (title and abstract); document type (article); source type (scholarly journals); coverage period (up to February 2023), language (English) |

| | | | | | | |
|---|---|---|---|---|---|---|
| assistants", "intelligence agents", "intelligence systems", "data analytics", "big data analytics", and "predictive analytics" | | "intelligence agents" OR "intelligence systems" OR "data analytics" OR "big data analytics" OR "predictive analytics") AND ("digital transformation" OR "digital disruption" OR "digital change"). | | language (English) | | |

*Search strategy.* The search process in the mentioned databases was limited to the Title, Abstract and Keywords according to their applicability. Consistent with many systematic reviews, only peer-reviewed academic journals were selected because of the significance of evidence from these resources (Dada, 2021). As mentioned earlier, this research aims to study how and under what circumstances AI can be managed within the DT process. For this reason, alongside the particular focus that DT has, as a business and managerial phenomenon on digital technologies and their related consequences for organisations, the primary focus of this study was on evidence from the business and management field as it could help to find the best possible evidence from the literature. Finally, the search included only those available published papers written in English. At the end of this stage, 830 papers were identified for further analysis.

*Exclusion criteria.* The identified papers in the previous stage were refined in this stage. First of all, duplicate studies were removed. Secondly, non-empirical studies were excluded as the main focus of this research was on empirical studies that gathered and analysed data by leveraging either qualitative and/or quantitative research methodologies. Thirdly, as this research was designed to study AI in the context of DT with a particular focus on how to manage AI within the DT process, technical papers in the AI field and its subfields, such as machine learning and deep learning, were not included in the final sample. Finally, because the main focus of the current research was on AI as a key driver of DT, papers that consider other types of disruptive technologies, such as IoT, blockchain and cloud computing, without any attention to AI and its associated concepts such as data analytics, automation, and chatbots, were removed. The final sample consisted of 33 articles.

### 2.2.2. Data analysis

To analyse the gathered data, content analysis was employed as one of the most recent widespread approaches for systematic literature review studies in the field of management (Dada, 2021; Dada, 2018). It is a flexible approach for yielding replicable insights by following a set of predefined techniques and has been used widely in several systematic analyses (Prasad, 2008; Krippendorff, 2019). The content analysis of the current study was done manually according to the method proposed by Prasad (2008) and inspired by the study conducted by Dada (2018). First, the main categories and sub-categories were identified in alignment with the aim of this study. To avoid any bias, the whole sample of final papers was analysed several times to define these categories. Second, by analysing key themes and concepts within the gathered empirical evidence, units of analysis as the smallest units of content to be coded into the identified categories and sub-categories were defined. Third, based on the common characteristics among these units and categories, they were linked to each other. For example, 'technological enablers' is the main category and 'infrastructure' is its sub-category. 'Robust infrastructure' and 'the segmentation and stability of processes', which appeared in the works done by Lozada et al. (2023) and Wang and Su (2021), respectively, were units of analysis coded into the aforementioned categories. To quantify the units of analysis, the number of times a given unit of analysis appeared in the sample was counted.

### 2.2.3. Results

All papers of the final sample were published over the past four years (2019-2023). As mentioned earlier, the starting year for coverage period was not restricted. Evidence revealed that the first paper conducted to study AI-based DT was published in 2019. Regarding the research method, almost half of the studies in the final sample employed a qualitative approach (n=16), followed by 15 and 2 articles that used quantitative and mixed methods as the research methodology, respectively. In terms of industry sector diversity, the category of multiple sectors was dominant (n=14), followed by manufacturing (n=5), finance and accounting (n=3), government and public administration (n=2), healthcare (n=2), telecommunication (n=1), sports (n=1), tourism (n=1), agriculture (n=1), retailing (n=1), banking (n=1), and tech (n=1) as the other mentioned industries among the final sample.

Table 2. Description of the articles included in the systematic literature review

| **Author (Year of publication)** | **Factor associated with AI-based digital transformation process addressed in the paper** | **Research design/ method/ data** | **Theoretical perspective** | **The kind of AI technology that has been used within the digital transformation process** | **Industry/ sector studied** | **Country of study/ regional focus** |
|---|---|---|---|---|---|---|
| Al-Khatib (2023) | Positive outcomes (i.e. innovation) | Quantitative/ survey | Resource based view (RBV) | Big Data Analytics Capability (BDAC) | Manufacturing | Jordan |
| Athota *et al.* (2023) | Positive outcomes (i.e. less uncertainty) | Qualitative/ interview | Attribution theory | Artificial Intelligence (AI) | Finance and Accounting | Australia |
| Christou *et al.* (2023) | Executive strategies (i.e. automation, augmentation | Qualitative/ interview | Customer experience | Intelligent Automation (IA) | Tourism | Cyprus |
| Lozada *et al.* (2023) | (1) Positive outcomes (i.e. innovation) (2) Technological enablers (i.e. data, infrastructure) (3) Organisational enablers (i.e. data driven culture, citizen data scientist, and organisational readiness) | Quantitative/ survey | Absorptive capacity theory | Big Data Analytics Capability (BDAC) | Multiple sectors (medium and low-technology companies, service companies) | Colombia |
| Lin *et al.* (2022) | (1) Positive outcomes (i.e. less uncertainty) (2) Technological enablers (i.e. data) | Quantitative/ survey | IT-enabled organisational capabilities | Big Data Analytics | Agriculture | China |
| Gao and Sarwar (2024) | Positive outcomes (i.e. innovation) | Quantitative/ survey | Dynamic capabilities theory | Big Data Analytics (BDA) | Multiple (i.e. manufacturing and logistics) | Pakistan |
| Atuahene *et al.* (2022) | (1) Technological enablers (i.e. data, infrastructure<br><br>(2) Organisational enablers data-driven culture, | Qualitative/ interview | Dynamic capabilities theory, Resource-based view (RBV) theory | Big data | Multiple (i.e. construction, consulting) | Australia |

| | | | | | | |
|---|---|---|---|---|---|---|
| | citizen data scientist)<br><br>(3) Environmental enablers (i.e. market pressure, competitor pressure, and governmental pressure) | | | | | |
| Bag *et al.* (2022) | Positive outcomes (i.e. customer engagement improvements) | Quantitative/ survey | Consumer engagement theory | Artificial Intelligence (AI) | Multiple (i.e. government and private sector) | India |
| Lin *et al.* (2022) | (1) Technological enablers (i.e. data)<br><br>(2) Organisational enablers (i.e. citizen data scientist) | Quantitative/ survey | Unknown | Deep learning | Healthcare | China |
| Papanagnou *et al.* (2022) | (1) Positive outcomes (i.e. less uncertainty)<br>(2) Technological enablers (i.e. infrastructure) | Qualitative/ interview | Dynamic capabilities theory | Big Data (BD) capabilities, Predictive analytics | Retailing | UK |
| Malik *et al.* (2022) | (1) Positive outcomes (i.e. work performance improvements)<br>(2) Negative outcomes (i.e. job-related issues) | Qualitative/ interview | Technostress perspective | Artificial Intelligence (AI) | Multiple industry (i.e. consulting, mechanical, electrical, computer science/IT industrial, construction/mining, electronics, financial services, and agriculture) | Multinational |
| Liew *et al.* (2022) | (1) Technological enablers (i.e. data, infrastructure)<br>(2) Organisational enablers (i.e. AI education for employees, citizen data scientist)<br>(3) Executive strategies (i.e. augmentation) | Qualitative/ interview | Technological reluctance theory | Big Data Analytics (BDA) | Finance and Accounting | New Zealand |
| | | | | | | Colombia |

| | | | | | | |
|---|---|---|---|---|---|---|
| Arias-Pérez and Cepeda-Cardona (2022) | Positive outcomes (i.e. innovation) | Quantitative/ survey | Knowledge-based view (KBV) theory, improvisation perspective | Artificial Intelligence (AI) | Multiple (i.e. financial and insurance, wholesale and retail, transportation and storage, human health and social work activities, computer programming, metal manufacturing, and office administrative and support activities) | |
| Arias-Pérez and Vélez-Jaramillo (2022b) | Organisational enablers (i.e. AI education for employees) | Quantitative/ survey | Transaction cost theory | Artificial Intelligence (AI) and Robotics | Multiple (i.e. financial and insurance, manufacturing and food products, wholesale and retail, human health and social work activities, computer programming, metal manufacturing, education, management consultancy activities, transportation and storage, office administrative and support activities, and other knowledge and less-knowledge intensive sectors) | Unknown |
| Moumtzidis *et al.* (2022) | (1) Technological enablers (i.e. data)<br>(2) Organisational enablers (i.e. AI education for employees) | Quantitative/ survey | Technology acceptance model | Big Data Analytics (BDA) | Telecommunication | Greece |
| Lufi *et al.* (2022) | (1) Technological enablers (i.e. infrastructure)<br>(2) Organisational enablers (i.e. leadership, AI education for employees, and organisational readiness)<br>(3) Environmental enablers (i.e. governmental pressures) | Quantitative/ survey | Technology adoption theory (Technology-Organisation-Environment [TOE] framework) | Big Data Analytics (BDA) | Manufacturing | Jordan |
| Egana-delSol *et al.* (2022) | Negative outcomes (i.e. job-related issues) | Quantitative/ survey | Task-based approach | Automation | Multiple (i.e. care, manufacturing, and services) | Chile, Colombia, Bolivia, and El Salvador |
| Ahn and Chen (2022) | Organisational enablers (i.e. AI | Quantitative/ survey | Diffusion of innovation theory, | | | US |

| | | | | | | |
|---|---|---|---|---|---|---|
| | education for employees) | | Technology Acceptance Model (TAM) | Artificial Intelligence (AI) | Government and public administration | |
| Chatterjee *et al.* (2022) | Organisational enablers (i.e. leadership, AI education for employees) | Quantitative/ survey | Resource-based view (RBV) theory | Artificial Intelligence (AI) | Multiple (i.e. manufacturing, service firms) | India |
| Arias-Pérez and Vélez-Jaramillo (2022a) | Organisational enablers (i.e. AI education for employees) | Quantitative/ survey | Knowledge-based view (KBV), transaction cost theory | Artificial Intelligence (AI) | Multiple (i.e. manufacturing, financial and insurance, telecommunication, wholesale and retail trade, education, architectural and engineering, and other knowledge-intensive, and low knowledge-intensive services | Colombia |
| De Andrade and Tumelero (2022) | (1) Positive outcomes (i.e. efficiency improvements) | Qualitative/ case study | Evolutionary theory of innovation | Chatbots | Banking | Brazil |
| Bodendorf *et al.* (2021) | Executive strategies (i.e. augmentation) | Qualitative and quantitative | Cost management | Artificial Intelligence (AI)/ Machine Learning (ML) | Manufacturing | UK |
| Sobrino-García (2021) | Negative outcomes (i.e. ethical issues) | Qualitative/ interview | Public administration perspective | Artificial Intelligence (AI) | Government and public administration | Spain |
| Leitner-Hanetseder *et al.* (2021) | Executive strategy (i.e. automation, augmentation) | Qualitative/ interview | Actor perspective on tasks and roles | Artificial Intelligence (AI) | Finance and Accounting | Austria, Finland, and the UK (ACRN Oxford Research Centre) |
| Ballestar *et al.* (2021) | (1) Positive outcomes (i.e. less uncertainty, work performance improvements)<br><br>(2) Negative outcomes (i.e. job-related issues) | Quantitative/ data science approach based on the ESEE dataset which consists of data from the Spanish manufacturing business from 1990 to 2015 | Technology adoption perspective | Robotics | Manufacturing | Spain |
| Wang and Su (2021) | (1) Technological enablers (i.e. infrastructure)<br>(2) Organisational enablers (i.e. leadership, | Qualitative/ Multiple case study | Technology adoption theory (Technology-Organisation Environment [TOE] framework) | Artificial Intelligence (AI) | Manufacturing | China |

| | | | | | | |
|---|---|---|---|---|---|---|
| | data-driven culture, and AI education for employees) (3) Environmental enablers (i.e. governmental pressure, market pressure, and competitors' pressure) | | | | | |
| Frick *et al*. (2021) | Organisational enablers (i.e. leadership) | Qualitative and quantitative<br><br>Interviews, survey | Empowering leadership perspective | Artificial Intelligence (AI) | Multiple (i.e. financial services, tattoo and body, and capital projects and infrastructure) | Unknown |
| Burstrom *et al.* (2021) | Executive strategies (i.e. co-creation) | Qualitative/ multiple case study | Business model innovation perspective | Artificial Intelligence (AI) | Multiple (i.e. manufacturing, mining) | Sweden |
| Sjödin *et al.* (2021) | (1) Technological enablers (i.e. data, infrastructure) (2) Organisational enablers (i.e. AI education for employees, citizen data scientist) (3) Executive strategies (i.e. co-creation) | Qualitative/ case study | Digital servitisation, business model innovation | Artificial Intelligence (AI) | Multiple (i.e. manufacturing, mining, shipping, and construction) | Sweden |
| Leone et al. (2021) | Executive strategies (i.e. co-creation) | Qualitative/ case study, interview | Value co-creation | Artificial Intelligence (AI) | Healthcare | US |
| Plattfaut and Koch (2021) | (1) Organisational enablers (i.e. AI education for employees) (2) Environmental enablers (i.e. customer pressure, market pressure) | Qualitative/ grounded theory study | Technology acceptance and adoption perspective | Robotic Process Automation (RPA) and Artificial Intelligence (AI) | Sports (i.e. soccer clubs) | Germany |
| Magistretti *et al.* (2019) | Executive strategies (i.e. co-creation) | Qualitative/ case study | General purpose technology insight | Artificial Intelligence (AI) | Tech | Unknown |
| Hartley and Sawaya (2019) | (1) Technological | Qualitative/ interviews | Technology adoption perspective | Robotic Process Automation (RPA), | Multiple (i.e. manufacturing and service firms) | Unknown |

| | | | | | | |
|---|---|---|---|---|---|---|
| | enablers (i.e. infrastructure) (2) Organisational enablers (i.e. leadership) | | | Artificial Intelligence (AI)/ Machine Learning | | |

Empirical findings on managing AI within DT are focused around six main building blocks: (1) technological enablers; (2) organisational enablers; (3) environmental enablers; (4) execution strategies; (5) positive outcomes; and (6) negative outcomes. These factors and their relationships are discussed in the following sections. Evidence from the review indicates two groups of positive and negative potential outcomes associated with using AI for the DT of organisations.

*Positive outcomes*

The potential benefits expected from using AI for DT purposes were found in 11 studies (Al-Khatib, 2023; Athota et al., 2023; Lozada et al., 2023; Lin et al., 2022; Gao and Sarwar, 2024; Papanagnou et al., 2022; Malik et al., 2022; Arias-Pérez and Cepeda-Cardona, 2022; De Andrade and Tumelero, 2022; Bag et al., 2022; Ballestar et al., 2021).

Four studies (Al-Khatib, 2023; Lozada et al., 2023; Gao and Sarwar, 2024; Arias-Pérez and Cepeda-Cardona, 2022) found that using capabilities provided by AI is positively related to innovation at the functional level (n=1) and organisational level (n=3). At the functional level, the supply chain was studied as a unit of analysis, while at the organisational level, innovation in products and processes, performance, and improvisation were considered. All these studies employed a quantitative research method. Dynamic capabilities and social capital theory, improvisation perspective and knowledge-based view of the firms (KBV), absorptive capacity theory and the resource-based view of firms (RBV) are the theoretical lenses used in these studies. Despite the differences between these perspectives, all of them concentrate on the capabilities required to be innovative, and this matter suggests that AI, as technological progress, can be used as such a resource. One of these studies (Al-Khatib, 2023) was carried out in the manufacturing sector, and the rest of them were conducted in multiple industries (Lozada et al., 2023; Gao and Sarwar, 2024; Arias-Pérez and Cepeda-Cardona, 2022). These findings altogether suggest that DT based on AI's competencies enables organisations to be more innovative. For example, findings from a study done by Lozada et al. (2023) depicted how this transformation affects innovation capabilities at the organisational level through enhancing product innovation. These findings revealed how AI-based DT enables organisations to analyse big data to find hidden and novel patterns about customers' needs, and consequently incorporate these non-declared needs into their current products.

Quantitative studies done by Bag et al. (2022) and De Andrade and Tumelero (2022) reveal that DT based on AI can cause improvements in customer engagement and organisations' efficiency, respectively. For example, regarding enhanced customer engagement, a study conducted by Bag et al. (2022) demonstrated that AI technologies deployed on social media platforms significantly enhance customer engagement by enabling organisations to deliver personalised offerings through real-time analysis of customer behaviour patterns. The unit of analysis for both studies was customers. This matter indicates the importance of the customers as the final recipient of any advantages that AI can give organisations. The theoretical perspectives of these studies were different. While in the first study, customer engagement theory was employed to study how AI can affect the emotional and satisfying relationship between organisations and their customers, the latter used the evolutionary theory of innovation to study the efficiency improvements in customer services through AI-based DT. The sectoral focuses of the aforementioned studies were banking and multiple sectors, respectively.

Findings from four studies (Papanagnou et al., 2022; Lin et al., 2022; Athota et al., 2023; Ballestar et al., 2021) indicate that organisations that incorporate AI into their DT processes encounter less degree of uncertainty in their operations. The first study reported that agriculture firms that used AI had much more stable and longer alliance relationships with their key partners, farmers. AI and Big Data Analytics Capabilities (BDAC) provide both sides of this alliance with valuable insight into each other's actions and plans. Consequently, this information can decrease the ambiguity surrounding this partnership and makes it much more stable.

The second piece of evidence related to less uncertainty, as a positive outcome of AI-based DT, is lessening the consequences of human bias. Decision-making, a process that relies on human cognition, is an inevitable function of any organisation. In this process, the potential biases associated with human cognition can cause serious concerns, particularly in areas such as the financial sector, where any fault may have some adverse consequences (Baker et al., 2017). A study conducted by Athota et al. (2023) found that due to AI's capabilities to work with a huge volume of data at a frantic pace and perform complex calculations, financial planners can utilise AI to overcome their cognitive biases and make unbiased decisions.

The last identified evidence from the review related to AI competencies to overcome uncertainties is resilience capability improvements. Unfavourable events, such as the Covid-19 pandemic, can cause many disruptions in the world (Queiroz et al., 2020). In such a context, resilience is a phenomenon that focuses on organisations' abilities to survive and return to at least the previous level of performance by overcoming these disruptions (Tukamuhabwa et al., 2017; Ambulkar et al., 2016). To possess and utilise this resilience, the process of environmental data has a significant role. From this point of view, findings from the literature indicate that organisations can improve their resilience capabilities through AI-based DT due to AI algorithms' power to extract required patterns from the huge volume of data. Regarding the research method, most findings were reported in studies that employed qualitative research method (n=3), followed by the quantitative approach (n=1). The aforementioned studies were conducted in the finance and accounting, agriculture, retailing, and manufacturing sectors.

From a theoretical perspective, studies that reported less uncertainty as a positive outcome of AI-based DT can be categorised into two distinct groups. The first group focused on potential capabilities that organisations can possess through a DT based on AI (Braojos et al., 2019; Teece, 2018; Diaz-chao et al., 2015). The employed theoretical lenses for these studies were dynamic capability theory, IT-enabled organisational capabilities, and technology adoption perspective. The mutual focus of these theories is the role of technologies in providing organisations with capabilities that enable them to gain or sustain their completive advantages, consistent with what organisations look for through their DT (Naimi-Sadigh et al., 2022). The second group of studies consists of one study (Athota et al., 2023) conducted from the attribution theory perspective. Attribution theory focuses on how individuals interpret their environment and its related events (Kelley and Michela, 1980). This study used this theoretical lens to investigate how AI can help decision-makers to overcome their cognitive biases due to the limits of the human brain in processing huge volumes of data.

The last group of potential benefits of AI-based DT found is work performance improvements. Two studies conducted by Ballestar et al. (2021) and Malik et al. (2022) reported this positive outcome. These studies reveal that due to the great potential that AI algorithms have for automating routine tasks, employees' time can be freed from mundane tasks. This matter can enable employees to be more innovative and productive as they have much more time to focus on more important tasks that require human intelligence and creativity, and consequently, job performance can be improved. Regarding the research method, quantitative and qualitative methods were employed in these studies. The industrial contexts of these studies were manufacturing and multiple sectors (e.g. computer science/IT industrial, construction/mining, electronics).

*Negative outcomes*

Despite the positive outcomes mentioned earlier, adverse consequences related to AI-based DT were identified in four studies. Regardless of the context of the study and the research methodologies used, findings suggest that using AI for DT purposes can increase the risk of privacy and security problems, cause ethical concerns, and raise job-related issues.

Findings related to job issues were reported in three studies (Malik et al., 2022; Egana-delSol et al., 2022; Ballestar et al., 2021). As mentioned above, from the job performance perspective, there are some opportunities associated with AI-based DT. However, despite these benefits, adverse outcomes such as job loss, technostress, and an increase in staffing costs are inevitable consequences. These problems can happen because of the AI's potential to automate routine tasks and replace employees who do these tasks, increasing the workload and complexity, job insecurity that may arise because of AI's disruptions, and finally, the essential costs for training staff who should be qualified to work in the era of AI.

Data are crucial inputs of AI algorithms that could be vulnerable to security and privacy issues. Moreover, the process through which these inputs are transformed into solutions is vague and may make any output biased, opaque, and even harmful without any legal responsibility. For these reasons, security and ethical issues are other kinds of negative outcomes related to AI-based DT. Evidence of these consequences was reported in studies done by Sobrino-García (2021) and Malik et al. (2022).

*Executive strategies*

Evidence related to positive and negative outcomes points toward the necessity of understanding how organisations should undergo DT based on AI's competencies. The review shows a range of strategies employed for AI-based DT. These strategies are important as they reveal how and under what circumstances organisations can utilise AI to realise their DT purposes.

Executive strategies for AI-based DT were reported in eight studies (Christou et al., 2023; Bodendorf et al., 2022; Liew et al., 2022; Leitner-Hanetseder et al., 2021; Burström et al., 2021; Sjödin et al., 2021; Leone et al., 2021; Magistretti et al., 2019). These strategies can be categorised into three broad types: (1) automation, (2) augmentation, and (3) co-creation.

Qualitative studies conducted by Christou et al. (2023) and Leitner-Hanetseder et al. (2021) in the tourism and finance/accounting sectors, respectively, reported automation as the initial strategy that can be adopted by organisations for using AI within their DT journey. This strategy can be considered as the starting point for using AI by organisations because it does not need sophisticated algorithms and knowledge, and organisations can follow it in specific areas without any consequences for other functions' performance. This approach for using AI in narrow areas indicates the functional approach of this strategy. According to this approach, AI can be utilised to achieve specific goals in particular areas by automation of routine and mundane tasks. Findings from the review introduced the room booking process in the tourism industry and data recording/collecting in the finance and accounting sectors as two examples of this strategy. In the context of the tourism industry and room booking process, this approach allows adopters to automate the entire booking process. For example, AI-based chatbots function very efficiently in handling the process from the initial stages where customers propose their preferences, to retrieving available options and completing the booking.

The next strategy identified through the review is augmentation. This strategy belongs to the higher level of AI utilisation for DT. At this level, organisations not only use AI to automate tasks but also utilise it to augment human experts. In such a context, the main focus should be devoted to the potential collaboration between AI and human experts rather than their competition and replacement. It means that any proposed solutions from AI algorithms are supposed to augment and assist human experts in playing their roles. One of the best examples of this strategy is the application of AI algorithms to augment radiologists for interpreting images (Hosny et al., 2018). In such a setting, AI-based solutions integrated into the radiology workflow can spot and highlight areas with abnormalities and potential tumours. This workflow reduces diagnostic times from days to hours, increases reporting accuracy, and allows clinicians to focus on complex cases. It is worth mentioning that at this level, human experts still play a critical role and are responsible for controlling AI-proposed solutions. This strategy was reported in four studies (Christou et al., 2023; Liew et al., 2022; Bodendorf et al., 2021; Leitner-Hanetseder et al., 2021), most of which employed qualitative research methods.

Two of these studies were conducted in the finance and accounting industry, followed by agriculture and manufacturing.

Four qualitative studies conducted by Leone et al. (2021), Magistretti et al. (2019), Sjödin et al. (2021), and Burström et al. (2021) reported another strategy named co-creation for AI-based DT. This strategy looks at AI as a general-purpose technology whose functions cover broad areas, unlike the previous approaches that focused on using AI within specific and narrow contexts. From this perspective, AI algorithms are supposed to solve complex problems whose solutions rely on humans' interdisciplinary knowledge and expertise. The requirements and potential consequences of such transformation could be completely different from the situations where organisations focus on automation and augmentation strategies. In this regard, the co-creation strategy suggests that organisations should undergo fundamental changes regarding their business model and ecosystem to become ready for AI-based DT at this level. This strategy applies to contexts where multiple players collaborate jointly to co-create value. In such a context, technology providers in close collaboration with other stakeholders develop and deliver AI-based solutions that alter how value is created rather than merely augment humans or automate a given task. An illustrative example for this strategy are the cases described in Leone et al. (2021), one of the reviewed studies that reported this strategy. As demonstrated in this work, a technology service provider in a joint effort with hospital experts focused on designing and implementing AI-based solutions that redesign the whole workflow. As shown, this is a context where the outcomes and contributions of AI-based solutions cover the broader ecosystem and the whole business model of organisations that follow AI-based DT with this strategy.

All the discussed strategies indicate how, and by which approach organisations can manage their AI-based DT. It is worth mentioning that these strategies can be evolutionarily adopted by organisations. This means organisations that use augmentation strategies have already leveraged the automation approach, and in the same way, organisations that follow their AI-based DT’s goal by co-creation approach are able to implement two simpler strategies. Business models, business model innovation and servitisation, value co-creation, and ecosystems are concepts that were used as theoretical perspectives in studies related to the co-creation approach. Employing these theoretical lenses indicates that, unlike the automation and augmentation strategies, utilising AI within the DT process by following the co-creation strategy requires holistic approaches. According to this approach, organisations should focus on required changes and justifications in their business model and ecosystem in order to enable AI-based DT.

*Enablers*

The review identifies three broad categories of enablers that affect organisations' AI-based DT. These enablers can be categorised as technological enablers, organisational enablers, and environmental enablers. These enablers and their associated factors are discussed below.

*Technological enablers*

Findings from 11 studies (Lozada et al., 2023; Lin et al., 2022; Atuahene et al., 2022; Lin et al., 2022; Liew et al., 2022; Moumtzidis et al., 2022; Lutfi et al., 2022; Papanagnou et al., 2022; Wang and Su, 2021; Sjödin et al., 2021; Hartley and Sawaya, 2019) reveal two groups of technological factors entitled (1) data and (2) infrastructure as critical factors that can affect AI-based DT.

The necessity of having access to adequate and high-quality data as critical requirements that AI algorithms are supposed to use for DT was reported in seven studies (Lozada et al., 2023; Lin et al., 2022; Atuahene et al., 2022; Lin et al., 2022; Liew et al., 2022; Moumtzidis et al., 2022; Sjödin et al., 2021). Irrespective of the data sources that can exist either outside or inside of the organisation, most of these studies focused on the quality of data. Regarding the research method, four studies employed qualitative research methods, and three studies used quantitative research methods. These studies were conducted in a wide range of sectors, such as agriculture, retailing, healthcare, finance and accounting, telecom, and manufacturing. Consistent with different works done in the literature on big data (Corte-Real et al., 2020; Ghasemaghaei, 2019; Abbasi et al., 2016; Wixom and Todd, 2005), this matter shows that regardless of the industry, data volume and data quality have the important impact on effective use of AI within the DT process.

After gathering the high-quality data, storing, preparing, and processing these data are essential tasks that depend on robust and suitable infrastructures and facilities. Eight studies (Lozada et al., 2023, Atuahene et al., 2022; Papanagnou et al., 2022; Liew et al., 2022; Lutfi et al., 2022; Wang and Su, 2021; Sjödin et al., 2021; Hartley and Sawaya, 2019) that mainly employed qualitative research method reported the importance of this issue. These findings indicate that to overcome associated challenges with data volume and the complexity of their processing, well-developed infrastructures are required. Such an essential infrastructure is not only limited to hardware aspects. In this regard, a qualitative study by Wang and Su (2021) in the manufacturing industry suggests that the structures of operations that are supposed to be transformed with AI are as important as physical infrastructure because of the potential impact that they may have on the volume of required data and the complexity of their processing. They found that the extent to which manufacturing operations are stable and can be segmented is positively related to the success rate of AI incorporation for DT. The variety of industrial contexts of these studies indicates that irrespective of the industrial type, the infrastructure factor has a critical impact from the perspective of technological enablers for AI-based DT.

In all, the identified evidence indicates that data and infrastructure required for managing and exploiting these data are critical factors that should have enough quality to assist organisations in using AI within their DT journeys.

*Organisational enablers*

Evidence from the 15 reviewed studies (Lozada et al., 2023; Atuahene et al., 2022; Lin et al., 2022; Liew et al., 2022; Arias-Pérez and Vélez-Jaramillo, 2022a; Moumtzidis et al., 2022; Lutfi et al., 2022; Ahn and Chen, 2022; Chatterjee et al., 2022; Arias-Pérez and Vélez-Jaramillo, 2022b; Wang and Su, 2021; Sjödin et al., 2021; Frick et al., 2021; Hartley and Sawaya, 2019; Plattfaut and Koch, 2021) reveal another group of factors that can influence AI-based DT, entitled organisational enablers. Unlike the technical enablers, constituent factors of this category - leadership, data-driven culture, AI education for employees, citizen data scientists, and organisational readiness - are more focused on the organisational aspects of AI-based DT.

Qualitative studies conducted by Hartley and Sawaya (2019) and Wang and Su (2021) reveal the positive impact of having a visionary, clear roadmap and support from the manager, on AI-based DT, respectively. Also, the importance of leadership support was found in two quantitative studies conducted by Chatterjee et al. (2022) and Lutfi et al. (2022). The significant influence of leadership was reported in another study done by Frick et al. (2021). However, unlike the aforementioned studies, work by Frick et al. (2021) found that empowering leadership style is not suitable in the era of AI. This study indicates that because of the unfamiliarity of employees with AI as a novel concept and the potential disruption that AI may cause, preparing a stable and consistent environment could be much more helpful than delegating high responsibility to employees. Among these five studies, three pieces of work employed a technology adoption perspective (i.e. Technology-Organisation-Environment [TOE] framework), and two of them employed RBV and empowering leadership style as the theoretical perspectives. The sectoral context of four of these studies was multiple industries, and one of them was conducted in the manufacturing industry. Altogether, most of these findings indicate a positive relationship between support from leadership and managers and successful AI-based DT.

The review further reveals the importance of data-driven culture that should be promoted within organisations when they attempt to utilise AI within DT process. Evidence of this factor was reported in three studies (Lozada et al., 2023; Atuahene et al., 2022; Wang and Su, 2021). According to these findings, organisations should utilise data and the extracted knowledge from these data across their whole functions rather than a few areas. In other words, when data and their associated insights cause positive outcomes on specific occasions, they should be transferable to other areas. This approach is consistent with the absorptive capacity theory employed in the quantitative study done by Lozada et al. (2023). From the absorptive capacity perspective, data-driven culture can enable organisations to utilise AI to exploit external data for gaining and sustaining competitive advantages. Findings from the review further reveal that RBV and dynamic capability theories and technology adoption perspective (i.e. TOE framework) were other theoretical perspectives employed in two qualitative studies conducted by Atuahene et al. (2022) and Wang and Su (2021), respectively. These theories indicate the importance of data-driven culture as a critical capability that can affect AI-based DT.

Ten studies (Liew et al., 2022; Arias-Pérez and Vélez-Jaramillo, 2022a; Moumtzidis et al., 2022; Lutfi et al., 2022; Ahn and Chen, 2022; Chatterjee et al., 2022; Arias-Pérez and Vélez-Jaramillo, 2022b; Sjödin et al., 2021; Wang and Su, 2021; Plattfaut and Koch, 2021) from the literature indicate the necessity of AI education for employees from two different perspectives.

The first group of studies consists of two qualitative research conducted by Wang and Su (2021) and Liew et al. (2022) in the manufacturing and finance/accounting sectors, respectively. They found that as employees are supposed to work with AI as a novel technology, they should learn how AI-based systems work and can assist them. Theoretical perspectives employed in these two studies were technology reluctance theory and technology adoption perspective (i.e. TOE framework). In a study by Liew et al. (2022), reluctance theory was employed as a theoretical lens to find potential resistance to adopting AI in auditing organisations. However, this study could not find any reluctance from employees to accept AI and surprisingly found that the studied organisations were ready to start training programs to teach their staff how to exploit AI's capabilities. The main focus of these studies was on the importance of learning the technical aspects of AI as a new technology.

However, the second group of studies went further on technical factors and discussed the education factor from the users' perspective. Evidence from eight studies shows that employees' awareness about AI and its consequences (Arias-Pérez and Vélez-Jaramillo, 2022a; Arias-Pérez and Vélez-Jaramillo, 2022b), staff willingness to use AI (Ahn and Chen, 2022), perceived value and ease of use (Ahn and Chen, 2022; Chatterjee et al., 2022; Sjödin et al., 2021; Moumtzidis et al., 2022), and perceived advantages (Lutfi et al., 2022; Plattfaut and Koch, 2021) affect AI-based DT positively, while perceived insecurity and complexity (Lutfi et al., 2022) has a negative impact. In this regard, organisations should run training programs to provide their employees with the required information about the aforementioned factors. Most of these studies applied the quantitative research method (n=6), and only two studies utilised the qualitative research method. Multiple industries (n=4), telecom industry (n=1), sports industry (n=1), manufacturing industry (n=1), and government and public administration (n=1) were the industrial contexts of these studies.

Related to staff issues, the review further identifies the required skills among employees of the organisation that deal with AI-based DT. The evidence about this factor was reported in five studies (Lozada et al., 2023; Liew et al., 2022; Atuahene et al., 2022; Lin et al., 2022; Sjödin et al., 2021). Findings show that whether organisations outsource technical aspects of AI-based DT or not, data science skills are essential for employees who contribute towards AI-based DT. Employees with these skills can be called citizen data scientists (Liew et al., 2022). Three of the aforementioned studies used qualitative research methods, and two studies applied a quantitative approach. The contexts of these studies were as diverse as manufacturing, healthcare, finance and accounting, and multiple sectors.

The final identified factor related to this type of enabler is organisational readiness. Quantitative studies conducted by Lutfi et al. (2022) and Lozada et al. (2023) in multiple industries found organisational readiness as an important factor whose major focus is on required capabilities for providing the technological and organisational enablers. From the perspective of absorptive capacity theory and technology adoption theory (i.e. TOE framework), financial and managerial capabilities were identified as required capabilities for providing other technological and organisational enablers for AI-based DT.

*Environmental enablers*

The last group of enablers reported in four studies are environmental enablers. This group of enablers is associated with factors that exist in the organisations' ecosystems and are usually out of the organisations' control.

Findings from the qualitative study done by Plattfaut and Koch (2021) reveal environmental factors - perceived market pull and perceived supporter perception - that can affect the incorporation of AI into the DT journey in the sports industry. Perceived market pull consists of two sub-factors named sponsor support and competitors pressure. From this perspective, the financial support that sponsors can provide and the extent to which competitors are interested in using novel technologies like AI are strong incentives that can affect AI-based DT. Also, evidence from this study indicates that the perceived supporter perception (i.e. customer support) has a negative relationship with the incorporation of AI by sports organisations because of fear of the potential mismatch that may exist between the fans' perception of the brand and AI as a cutting-edge technology, specifically when they have had a good record in different tournaments.

In other studies conducted by Atuahene et al. (2022), Lutfi et al. (2022), and Wang and Su (2021), similar factors such as enforcements that may come from the ecosystem's stakeholders and data-driven culture that may surround the industry, governmental support and forces, and market and competitor pressures were identified as effective factors that may affect AI's incorporation into DT. Most of these studies employed technology acceptance theories (i.e. TOE framework) that have a primary focus on the influence of environmental factors for utilising emerging technologies.

## 2.3. Discussion

Significant progress in data storing and computing power has increased the importance of AI as a technology that is able to assist organisations for DT (Grønsund and Aanestad, 2020). However, AI's specific attributes have caused ambiguities around this transformation. This review has developed a conceptual model that provides better information about these issues. This model demonstrates possible strategies for AI-based DT, key organisational, technological, and environmental enablers for such a transformation, and associated positive and negative outcomes.

*Research implications*

Regardless of the industrial sector, utilising AI by organisations within DT process has several positive outcomes. Most studies that found positive outcomes employed theoretical lenses such as the resource-based view of the firm (RBV), dynamic capabilities, and knowledge-based view of the firm (KBV), whose main focus are on the resources and capabilities that can give firms competitive advantages. These indicate the role of AI as a critical resource that can enable organisations to gain competitive advantages by using it within their DT processes.

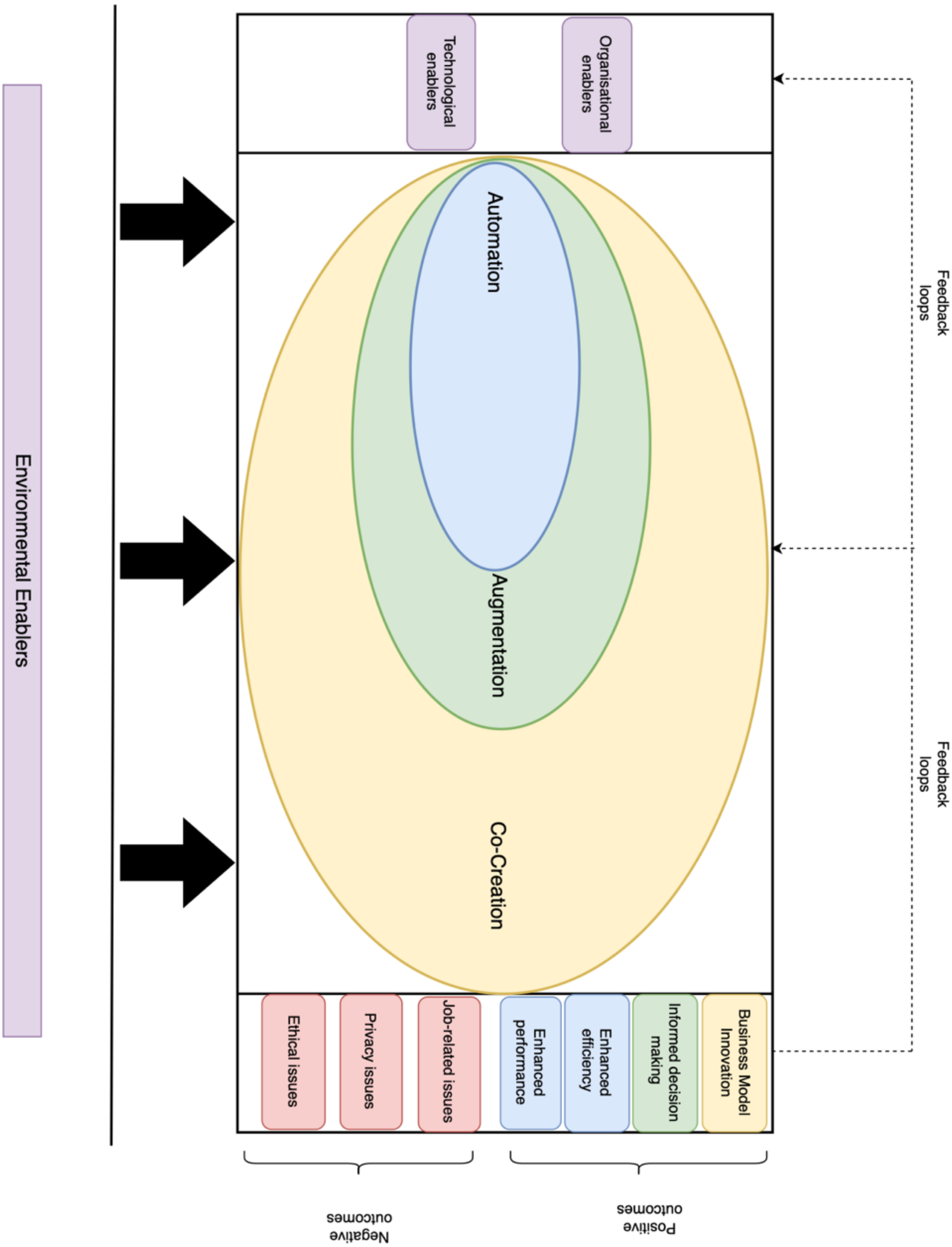
The negative outcomes reported in the review were mostly discussed from work-related perspectives. These studies were conducted in a wide range of industrial sectors, such as manufacturing, transportation, and wholesale. This frequent use of work-related perspectives across different sectors indicate that irrespective of the industry, job-related issues of AI-based DT are among the most important concerns that require significant attention. Ethical concerns were studied in only one research conducted in the public sector. This number shows the higher priority that has been given to the economic consequences of AI rather than to ethical issues.

This review further reveals a range of potential strategies for AI-based DT. Studies that reported automation and augmentation strategies for AI-based DT employed diverse theoretical perspectives, such as the theory of technological turbulence, cost management theory, and customer experience perspective. The diversity of these theoretical lenses can be interpreted from the functional approaches of automation and augmentation strategies since these strategies are usually focused on using AI in specific and narrow functions for automating routine tasks (i.e. booking rooms in the hotel industry) and augmenting human experts (i.e. assisting radiologists in interpreting images). For this reason, the theoretical lenses that support these strategies can be contextual. Consistent with this argument, unlike the aforementioned strategies, the co-creation strategy, as an approach whose major focus is on fundamental changes in the business model and ecosystem, was mostly discussed from a unified and particular theoretical perspective (i.e. business model and ecosystem).

This review identified a range of key enablers for AI-based DT. Irrespective of the different types of these enablers, particular kinds of theories that focus on how organisations can incorporate novel technologies and gain competitive advantages, such as absorptive capacity theory, RBV, KBV, technology adoption theories (i.e. TOE framework), and dynamic capability theory, were used across the vast majority of these studies. The mutual characteristics that these theories share indicate the critical role of AI in enabling organisations to gain competitive advantages. Indeed these enablers are essential to benefit from the associated merits of AI-based DT and lessen their severe effects.

Finally, findings from the review informed the design of a model that can assist organisations to have digital transformation based on AI's capabilities (Figure 1). As shown below, a combination of different organisational and technological enablers are required when organisations seek to utilise AI for their DT's purposes. The proposed model demonstrates that based on what types of enablers organisations have and according to the goals they may set to achieve through their AI-based DT, three types of strategies can be adopted by organisations to fulfil their DT's ambitions. These strategies have an evolutionary approach. In other words, if a given organisation's primary strategy for AI-based DT is augmentation, at the same time it has the capability to utilise the automation strategy, and if co-creation is the central strategy of a given organisation, it is able to implement the other two types of strategies for its AI-based DT purposes. The proposed model also depicted another group of enablers entitled environmental enablers. As is shown in the model, unlike the organisational and technological enablers, this group of enablers consists of factors that can affect the whole process of the AI-based DT which are not necessarily controlled by the organisations. Finally, depending on what types of organisational and technological enablers are utilised by organisations, the adopted strategy for AI-based DT, and the types of environmental enablers that organisations should cope with, positive and negative outcomes can be expected. As shown in Figure 1, each strategy yields specific positive outcomes: automation results in enhanced performance and efficiency; augmentation leads to informed decision making; and co-creation fosters business model innovation. However, negative outcomes may occur regardless of what type of strategy is adopted. This implies that while specific strategies may be required to realise particular advantages of AI-based DT, organisations eventually encounter certain inevitable negative consequences regardless of their chosen strategy. This fact warrants careful consideration of these potential drawbacks when organisations manage their AI-based DT. The dotted lines link possible outcomes to strategy and the organisational/technological enablers demonstrate the feedback loops that enables organisations to consider the required revisions in their organisational/technological enablers and adopted strategies according to the achieved outputs.

Figure 1. A Conceptual Model for Managing AI within DT Process



*Practical implications*

Digital transformation may have some benefits and challenges for organisations. When organisations undergo AI-based DT, associated consequences can be more far-reaching than other digital technologies since AI has significant transformative power. The current review identifies a wide range of positive and negative outcomes that AI-based DT may have. Organisations can use these results to adopt a more realistic outlook on AI and its rewards and risks. Such a mindset enables organisations to benefit from AI's advantages while lessening its adverse effects and manage their AI-based DT process more efficiently.

Organisational enablers identified in this study allow organisations to go beyond technological aspects by considering organisational and managerial issues that have attracted less attention, despite their critical role in AI-based DT. The incorporation of novel technologies cannot guarantee success per se. For these technologies to be beneficial, they should be managed properly. The scope of this management goes beyond technical aspects, given that AI as a technology is associated with serious ethical and economic concerns. From this perspective, the identified organisational enablers help to facilitate AI-based DT and lessen the challenges and resistances. Furthermore, the noted environmental enablers allow organisations to adopt a more holistic approach for AI-based DT by considering the potential exerted pressure from their ecosystem.

Finally, according to the AI-based DT's focus, which can either use AI for functional transformation or treat it as a general-purpose technology, the proposed conceptual model can provide organisations with three different executive strategies, namely automation, augmentation and co-creation.

*Limitations and directions for future research*

This study is not without limitations. First, although considerable attempt was made to minimise bias with the systematic literature review (especially in terms of searching and selecting the articles), we are unable to state with certainty that there is no bias in the final sample. Second, since the proposed conceptual model and its associated factors are generic, drawing generalised findings from contextualized evidence is a potential limitation of the current review. Third, AI is an umbrella term, and there is no clear consensus on its definition. This scarcity imposed another limitation on this study, specifically for using AI-associated concepts, such as machine learning, deep learning, data analytics, and digital assistants, in search keywords. In this regard, this study, by drawing on the definition of AI as a technology that focuses on sophisticated algorithms' learning to perform certain tasks as intelligent as humans by exploiting extensive quantities of data (Baird and Maruping, 2021; Haenlein and Kaplan, 2019; Jordan and Mitchell, 2015), considered these types of concepts as kinds of AI technology because of the same functionality they have for learning intelligence behaviour to perform specific tasks by exploiting a huge volume of data.

Despite the limitations of the review, it provides opportunities for future research. First, a few sectors such as retailing, banking and healthcare have not been explored significantly. Scholars could consider undertaking research in these fields to study AI-based DT. Second, studies that focus on possible strategies for AI-based DT are few. This domain could provide interesting insights in further research. Finally, the findings of this study are generic. Researchers can use the proposed model in this study in specific domains and industries and update them with contextual characteristics.

### 2.4. Conclusion

The current study contributes to knowledge by proposing a conceptual model that indicates the main factors associated with AI-based DT. The evidence shows the superiority of theoretical perspectives, such as the resource-based view (RBV), knowledge-based view (KBV), absorptive capacity theory, dynamic capability theory, and technology adoption perspective, whose focus is on how organisations should exploit specific resources to gain competitive advantages. This study further makes contributions towards knowledge by proposing the potential approaches that organisations can adopt for using AI within their DT journey and the potential consequences that this adoption may have. AI and its transformative power can provide considerable opportunities and threats for organisations that should be used and avoided, respectively. The developed model, by proposing the important factors associated with AI-based DT, can assist organisations with reaping AI's rewards and help to lessen its severe outcomes.

## References


Abbasi, A., Sarker, S., & Chiang, R. H. (2016) Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems*, 17(2), 1-32.

Ahn, M. J., & Chen, Y. C. (2022) Digital transformation toward AI-augmented public administration: The perception of government employees and the willingness to use AI in government. *Government Information Quarterly*, 39(2), 101664.

AL-Khatib, A. W. (2023) The determinants of export performance in the digital transformation era: empirical evidence from manufacturing firms. *International Journal of Emerging Markets*, 19(10), 2597-2622.

Ambulkar, S., Blackhurst, J. V., & Cantor, D. E. (2016) Supply chain risk mitigation competency: an individual-level knowledge-based perspective. *International Journal of Production Research*, 54(5), 1398-1411.

Arias-Pérez, J., & Cepeda-Cardona, J. (2022) Knowledge management strategies and organizational improvisation: what changed after the emergence of technological turbulence caused by artificial intelligence? *Baltic Journal of Management*, 17(2), 250-265.

Arias-Pérez, J., & Vélez-Jaramillo, J. (2022a) Ignoring the three-way interaction of digital orientation, Not-invented-here syndrome and employee's artificial intelligence awareness in digital innovation performance: A recipe for failure. *Technological Forecasting and Social Change*, 174, 121305.

Arias-Pérez, J., & Vélez-Jaramillo, J. (2022b) Understanding knowledge hiding under technological turbulence caused by artificial intelligence and robotics. *Journal of Knowledge Management*, 26(6), 1476-1491.

Athota, V. S., Pereira, V., Hasan, Z., Vaz, D., Laker, B., & Reppas, D. (2023) Overcoming financial planners' cognitive biases through digitalization: A qualitative study. *Journal of Business Research*, 154, 113291.

Atuahene, B. T., Kanjanabootra, S., & Gajendran, T. (2022) Transformative role of big data through enabling capability recognition in construction. *Construction Management and Economics*, 41(3), 208-231.

Bag, S., Srivastava, G., Bashir, M. M. A., Kumari, S., Giannakis, M., & Chowdhury, A. H. (2022) Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking: An International Journal*, 29(7), 2074-2098.

Baird, A., & Maruping, L. M. (2021) The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS Quarterly*, 45(1), 315-341.

Baker, H. K., Filbeck, G., & Ricciardi, V. (eds.) (2017) *Financial behavior: Players, services, products, and markets*. Oxford: Oxford University Press.

Ballestar, M. T., Díaz-Chao, Á., Sainz, J., & Torrent-Sellens, J. (2021) Impact of robotics on manufacturing: A longitudinal machine learning perspective. *Technological Forecasting and Social Change*, 162, 120348.

Barroso, M., & Laborda, J. (2022) Digital transformation and the emergence of the Fintech sector: Systematic literature review. *Digital Business*, 2(2), 100028.

Bodendorf, F., Lutz, M., Michelberger, S., & Franke, J. (2022) An empirical investigation into intelligent cost analysis in purchasing. *Supply Chain Management: An International Journal*, 27(6), 785-808.

Boyd, R., & Holton, R. J. (2018) Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? *Journal of Sociology*, 54(3), 331-345.

Braojos, J., Benitez, J., & Llorens, J. (2019) How do social commerce-IT capabilities influence firm performance? Theory and empirical evidence. *Information & Management*, 56(2), 155-171.

Brynjolfsson, E., & McAfee, A. (2017) The business of artificial intelligence. *Harvard Business Review*, 7(1), 1-2.

Burström, T., Parida, V., Lahti, T., & Wincent, J. (2021) AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. *Journal of Business Research*, 127, 85-95.

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Jabeen, F. (2022) Digital transformation of organization using AI-CRM: From microfoundational perspective with leadership support. *Journal of Business Research*, 153, 46-58.

Christou, P., Hadjielias, E., Simillidou, A., & Kvasova, O. (2023) The use of intelligent automation as a form of digital transformation in tourism: Towards a hybrid experiential offering. *Journal of Business Research*, 155, 113415.

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2020) Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Information & Management*, 57(1), 103141.

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.

Dada, O. (2021) Curbing franchisee failure: A systematic review of the empirical evidence. *Journal of Small Business Management*, 61(4), 1991-2037.

De Andrade, I. M., & Tumelero, C. (2022) Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestão*, 29(3), 238-251.

Demirkan, H., Spohrer, J. C., & Welser, J. J. (2016) Digital innovation and strategic transformation. *IT Professional*, 18(6), 14-18.

Díaz-Chao, Á., Sainz-González, J., & Torrent-Sellens, J. (2015) ICT, innovation, and firm productivity: New evidence from small local firms. *Journal of Business Research*, 68(7), 1439-1444.

Egana-delSol, P., Bustelo, M., Ripani, L., Soler, N., & Viollaz, M. (2022) Automation in Latin America: Are Women at Higher Risk of Losing Their Jobs? *Technological Forecasting and Social Change*, 175, 121333.

Fitzgerald, M., Kruschwitz, N., Bonnet, D., & Welch, M. (2014) Embracing digital technology: A new strategic imperative. *MIT Sloan Management Review*, 55(2), 1-12.

Frick, N. R., Mirbabaie, M., Stieglitz, S., & Salomon, J. (2021) Maneuvering through the stormy seas of digital transformation: the impact of empowering leadership on the AI readiness of enterprises. *Journal of Decision Systems*, 30(2-3), 235-258.

Gao, J., & Sarwar, Z. (2024) How do firms create business value and dynamic capabilities by leveraging big data analytics management capability? *Information Technology and Management*, 25(3), 283-304.

Ghasemaghaei, M. (2019) Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems*, 120, 14-24.

Grønsund, T., & Aanestad, M. (2020) Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems*, 29(2), 101614.

Haenlein, M., & Kaplan, A. (2019) A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14.

Hakala, H. (2011) Strategic orientations in management literature: Three approaches to understanding the interaction between market, technology, entrepreneurial and learning orientations. *International Journal of Management Reviews*, 13(2), 199-217.

Hartley, J. L., & Sawaya, W. J. (2019) Tortoise, not the hare: Digital transformation of supply chain business processes. *Business Horizons*, 62(6), 707-715.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016) Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, 15(2), 123-139.

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. (2018) Artificial intelligence in radiology. *Nature Reviews Cancer*, 18(8), 500-510.

Jordan, M. I., & Mitchell, T. M. (2015) Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255-260.

Kelley, H. H., & Michela, J. L. (1980) Attribution theory and research. *Annual Review of Psychology*, 31(1), 457-501.

Kraus, S., Jones, P., Kailer, N., Weinmann, A., Chaparro-Banegas, N., & Roig-Tierno, N. (2021) Digital transformation: An overview of the current state of the art of research. *Sage Open*, 11(3), 1-15.

Krippendorff, K. (2019). *Content analysis : an introduction to its methodology* (4th edition.). SAGE Publications, Inc.

Leitner-Hanetseder, S., Lehner, O. M., Eisl, C., & Forstenlechner, C. (2021) A profession in transition: Actors, tasks and roles in AI-based accounting. *Journal of Applied Accounting Research*, 22(3), 539-556.

Leone, D., Schiavone, F., Appio, F. P., & Chiao, B. (2021) How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem. *Journal of Business Research*, 129, 849-859.

Liew, A., Boxall, P., & Setiawan, D. (2022). The transformation to data analytics in Big-Four financial audit: what, why and how? *Pacific Accounting Review*, *34*(4), 569-584.

Lin, S., Li, L., Zou, H., Xu, Y., & Lu, L. (2022) Medical Staff and Resident Preferences for Using Deep Learning in Eye Disease Screening: Discrete Choice Experiment. *Journal of Medical Internet Research*, 24(9), e40249.

Lin, S., Lin, J., Han, F., & Luo, X. R. (2022) How big data analytics enables the alliance relationship stability of contract farming in the age of digital transformation. *Information & Management*, 59(6), 103680.

Lozada, N., Arias-Pérez, J., & Edwin Alexander, H. G. (2023) Unveiling the effects of big data analytics capability on innovation capability through absorptive capacity: why more and better insights matter. *Journal of Enterprise Information Management*, 36(2), 680-701.

Lutfi, A., Alsyouf, A., Almaiah, M.A., Alrawad, M., Abdo, A.A.K., Al-Khasawneh, A.L., Ibrahim, N., & Saad, M. (2022) Factors influencing the adoption of big data analytics in the digital transformation era: case study of Jordanian SMEs. *Sustainability*, 14(3), 1802.

Magistretti, S., Dell'Era, C., & Petruzzelli, A. M. (2019) How intelligent is Watson? Enabling digital transformation through artificial intelligence. *Business Horizons*, 62(6), 819-829.

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2022) Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower*, 43(2), 334-354.

Matt, D. T., Pedrini, G., Bonfant, A., & Orzes, G. (2022) Industrial digitalization. A systematic literature review and research agenda. *European Management Journal*, 41(1), 47-78.

Moumtzidis, I., Kamariotou, M., & Kitsios, F. (2022) Digital transformation strategies enabled by internet of things and big data analytics: The use-case of telecommunication companies in Greece. *Information*, 13(4), 196.

Naimi-Sadigh, A., Asgari, T., & Rabiei, M. (2022). Digital transformation in the value chain disruption of banking services. *Journal of the Knowledge Economy*, 13(2), 1212-1242.

Papanagnou, C., Seiler, A., Spanaki, K., Papadopoulos, T., & Bourlakis, M. (2022) Data-driven digital transformation for emergency situations: The case of the UK retail sector. *International Journal of Production Economics*, 250, 108628

Parris, D. L., & Peachey, J. W. (2013) A systematic literature review of servant leadership theory in organizational contexts. *Journal of Business Ethics*, 113(3), 377-393.

Plattfaut, R., & Koch, J. (2021) Preserving the legacy–Why do professional soccer clubs (not) adopt innovative process technologies? A grounded theory study. *Journal of Business Research*, 136, 237-250.

Prasad, B.D. (2008) Content analysis: A method of Social Science Research. In Lal Das, D.K. and Bhaskaran, V. (eds), *Research Methods for Social Work*. New Delhi: Rawat, 173-193.

Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2020) Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research*, 319(1), 1159-1196.

Rêgo, B. S., Jayantilal, S., Ferreira, J. J., & Carayannis, E. G. (2021) Digital transformation and strategic management: A systematic review of the literature. *Journal of the Knowledge Economy*, 13(4), 3195-3222.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021) How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, 134, 574-587.

Sobrino-García, I. (2021) Artificial intelligence risks and challenges in the Spanish public administration: An exploratory analysis through expert judgements. *Administrative Sciences*, 11(3), 102.

Teece, D. J. (2018) Business models and dynamic capabilities. *Long Range Planning*, 51(1), 40-49.

Tukamuhabwa, B., Stevenson, M., & Busby, J. (2017) Supply chain resilience in a developing country context: a case study on the interconnectedness of threats, strategies and outcomes. *Supply Chain Management*, 22(6), 486-505.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021) Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-900.

Vial, G. (2019) Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, 28(2), 1-27.

Wang, C. L., & Chugh, H. (2014) Entrepreneurial learning: Past research and future challenges. *International Journal of Management Reviews*, 16(1), 24-61.

Wang, Y., & Su, X. (2021) Driving factors of digital transformation for manufacturing enterprises: A multi-case study from China. *International Journal of Technology Management*, 87(2-4), 229-253.

Wixom, B. H., & Todd, P. A. (2005) A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, 16(1), 85-102.

## Chapter 3: Managing augmented intelligence in innovation practices: Evidence from knowledge-intensive start-ups

**Shayan Rashidi, Richard Williams, and Olufunmilola (Lola) Dada**

**Submitted to the special issue of AJG  rank 4 journal.**

**Abstract**

Competition, along with gaining and sustaining competitive advantages, has always been a main priority of organisations. To achieve such advantages, organisations need to constantly pursue innovation practices to make their offerings more distinguishable against their rivals. In this context, depending on how organisations create value and the types of resources they utilise for value creation, different types of innovation practices can be followed to gain and sustain competitive advantages. Drawing on the Knowledge-Based View (KBV) of the firm, one of the key resources utilised by a wide range of organisations, is knowledge. Across these organisations, innovation happens either through creation of new knowledge or utilisation of the current knowledge in a novel way. The creation and utilisation of knowledge, particularly in its tacit form, has always been viewed as the primary role of Human Intelligence (HI). However, with the emergence of Artificial Intelligence (AI) and its perception as a novel source of intelligence, this perspective may face new challenges. In this regard, the current research, by utilising a qualitative methodological approach, studied five knowledge-intensive start-ups to gain a better understanding of innovation practices when knowledge is treated as the main source of competitive advantage, and humans may no longer be the only intelligent agents. The findings informed the design of a conceptual model that demonstrates novel innovation patterns comprising of AI and HI, and a division of tasks between AI and HI, which illustrates AI's contribution towards the creation and utilisation of both tacit and explicit knowledge.

Key words: Innovation, Artificial Intelligence, Human Intelligence, Augmented Intelligence, Knowledge-based View of the Firm

### 3.1. Introduction

Technological innovation has long been recognised as a major source of competitive advantage for organisations (Teece, 1986). These innovations have consistently provided essential and robust tools that enable organisations to either enhance the efficiency of their existing operations and services or offer novel business solutions (Zott and Amit, 2010). Technological advancements such as Artificial Intelligence (AI), blockchain, and the Internet of Things (IoT) are among the most important emerging technologies expected to provide competitive advantages. In this context, AI seems more promising than the others because AI is not only capable of learning and exhibiting intelligent behaviour previously exclusive to humans through harnessing significant volumes of data but can also develop such intelligence more efficiently and in a more straightforward manner than traditional information systems technologies, whose functionality depends on defining massive rules and extensive programming efforts (Kordjamshidi et al., 2022; Haenlein and Kaplan, 2019; Goodfellow et al., 2016). These two unique characteristics have depicted an optimistic outlook for organisations' adoption of AI.

Gaining and sustaining a competitive advantage is not a novel and new-born concept. Indeed, it has been among the most crucial phenomena of management and organisational studies, regardless of whether such an advantage is provided by technological innovations or not. Despite the different perspectives adopted by distinct streams of research, they all aim to answer the question of why some organisations have better performance and position against their competitors. In such a context, one of the most prominent theoretical lenses focused on addressing this question is the knowledge-based view of the firm (KBV).

As an extension of the Resource-based View (RBV) of the firm, the Knowledge-based View (KBV) of the firm emerged as a concept that fundamentally reconceptualised the firm from a mere resource owner and processor to a knowledge-creating and knowledge-integrating entity (Grant, 1996; Kogut and Zander, 1992; Spender, 1996). This stream of knowledge has been shaped through seminal works by Grant (1996), Nonaka and Takeuchi (1995), and Kogut and Zander (1992), who collectively treat knowledge as the most strategic resource possessed and utilised by organisations to create and sustain competitive advantages. In the realm of the KBV, coordination and cooperation challenges around knowledge constitute two of the major pillars upon which this theory is built, both rooted in Simon's (1955) bounded rationality concept and the notion of specialised knowledge proposed to overcome limitations arising from human bounded rationality (Grant, 1996).

Given these fundamental limitations of bounded rationality, and coordination and cooperation challenges in the context of knowledge-based organisations, the adoption of AI by such organisations, as a technology that can exhibit human-like intelligence without having common human brain constraints, presents unprecedented opportunities. However, profiting from AI is not necessarily guaranteed by its mere adoption. This means that a given organisation cannot benefit from the advantages of emerging technologies, unless they are being used in an innovative manner (Brynjolfsson and Hitt, 1998), and this applies to AI as well. In this regard, one well-established perspective on how organisations can profit from digital technologies and advantages they provide is a work done by Teece (2010). As Teece (2010) argues, organisations, in order to benefit from digital technologies should innovate how they create, capture, and deliver value. Viewing organisations from the KBV perspective, knowledge creation and knowledge utilisation are two major underlying activities that shape value creation mechanism (Spender, 1992). Accordingly, a technology like AI provides knowledge-based organisations with advantages where these organisations innovate their knowledge creation and utilisation processes by incorporating AI. Yet, when AI is an enabler of such an innovation, organisations face with more complexity whose scope goes beyond a mere automation and common capabilities associated with digital technologies (Benbya et al., 2021; Baptista et al., 2020; Huysman, 2020). This is because AI can not only function as a technological tool to serve Human Intelligence (HI) who has the primary agency in creation and utilisation of knowledge, but can also be considered as a novel source of intelligence, capable of collaborating and working with HI in the form of augmented intelligence in knowledge related activities. In this context to address such a complexity, the current study is designed to answer the following research question: *How can augmented intelligence be managed in the innovation practices of knowledge-based organisations?*

The rest of the paper is structured as follows: first, the literature on AI and its augmentation role in the organisational context, and KBV as the theoretical lens adopted for this study are discussed. Then the utilised research method, including how data (i.e. case studies) are collected and analysed, is discussed. This is followed by introducing the discovered theoretical framework that demonstrates novel innovation practices and their corresponding setting for managing augmented intelligence. Finally, the theoretical and practical contributions that the current study has made are presented.

## 3.2. Literature Review

### 3.2.1. AI within an Organisational Context

AI and its ongoing progress have attracted significant attention over the past few years across a wide range of disciplines and sectors, such as healthcare (Issa et al., 2024; Abadie et al., 2023; Singha et al., 2023; Pham et al., 2024; Dicuonzo et al., 2023), retail (Chattaraman et al., 2024; Song and Kim, 2022), finance (Zhu et al., 2024; Rodgers et al., 2023; Upadhyay and Kamble, 2024), and professional services (Spring et al., 2022). Despite the lack of well-established consensus on the definition of AI, its autonomous ability to learn particular intelligent behaviours by exploiting an adequate volume of data without the considerable intervention of humans and leveraging these learned intelligences across different contexts with the least adjustment, is a feature that has been widely accepted (Baird and Maruping, 2021; Brynjolfsson and McAfee, 2017). Indeed, this autonomous ability to learn complex behaviours and tasks, which is in sharp contrast to usual approaches for designing information systems, is a unique distinguishable feature of AI that has enabled its increasing growth across a range of organisational functions (Csaszar and Steinberger, 2022). At the organisational level, automation and augmentation are the two well-known approaches that different organisations, regardless of their industrial sector, adopt to realise the potential benefits of AI within their operations. While the first approach focuses on AI's ability to take over HI's role in specific tasks, the latter looks for potential means for collaboration between HI and AI (Stelmaszak et al., 2025; Choudhary et al., 2023; Raisch and Krakowski, 2021). As the current study is particularly focused on augmentation rather than automation, the next section discusses the literature on the augmentation approach.

### 3.2.2. Augmented Intelligence

AI has great potential in automating a wide range of different tasks and processes (Balasubramanian et al., 2022). However, focusing on its augmentation role could be more beneficial, as this approach not only enables organisations to utilise capabilities associated with AI, but also allows them to exploit HI, which has always been considered as the main source of knowledge and intelligence. In this regard, and from different perspectives, a range of empirical and conceptual studies have been conducted in the literature on organisational aspects of AI. Depending on how collaboration between AI and HI can be managed, this literature introduced three main streams.

The first approach focuses on HI's role in training AI algorithms and validating their generated outputs. According to this approach, HI plays its role at two different levels. First, it contributes by providing and structuring the required data for designing AI algorithms. The importance of such a role is rooted in the fact that the performance and accuracy of any AI algorithms depend significantly on the quality and quantity of data. As a result, the more data and the higher quality of data can cause better performance. The role of HI is not only limited to the development stage. In this regard, the second level where HI plays its role is when the designed AI algorithms are implemented. At this level, HI is involved in observing and validating the output generated by AI. AI algorithms' outputs are not error-free as the data that are used to train them may be biased. These biases can affect the performance of AI algorithms and cause negative outcomes, specifically in contexts such as healthcare, where any error can come at the cost of humans' lives. Therefore, to be confident that AI is used safely with the lowest possible error, recruiting HI alongside AI could be helpful. This approach for teaming up between AI and HI has been discussed extensively in the literature through studies done by Ostheimer et al. (2021), Vellido (2020), Dellermann et al. (2019a), Dellermann et al. (2019b), and Holzinger (2016). The major assumption that underlies this stream of literature is the superior position of HI against AI, which causes it to become eligible to control and observe AI as a teammate.

Another group of studies carried out by Seeber et al. (2020), Murray et al. (2021), Dellermann et al. (2019b), and Jarrahi (2018), upon the assumption that across different areas both AI and HI have absolute advantages against each other, focused on how a given task can be divided between AI and HI. From this perspective, there are groups of tasks for which AI can outperform HI and vice versa (Agrawal et al., 2019). Adopting such an approach could be beneficial, as depending on the nature of tasks, it enables organisations to take advantage of related intelligence (i.e., HI or AI) and minimise its associated drawbacks. In this regard, one of the most common factors widely accepted in the literature as an influential factor in deciding whether a given task should be allocated to HI or AI is the extent to which the task is unusual. In other words, AI can be better for tasks whose contexts are more stable and usual, while HI can be more beneficial for tasks associated with more uncertainty and unforeseen circumstances. However, despite the particular emphasis that this stream of literature has on the significant impact of the tasks' nature on deciding whether a given task should be allocated to AI or HI, it did not provide a rich picture about task division between AI and HI since it only focused on whether a given task is either usual or exceptional. Only the seminal work done by Shrestha et al. (2019) was found to have considered some wider range of factors (such as decision search space, interpretability of problem, decision-making speed) that can affect how a suitable candidate to perform a given task can be chosen.

The last approach that has been recently coined in the literature in the study of Choudhary et al. (2023) applies to the contexts where not only AI is inferior to HI, but HI is also associated with critical errors and inaccuracies that can significantly affect the output of their collaboration. An ensemble approach is what has been proposed for these types of situations (Choudhary et al., 2023). According to this approach, in contrast to the task division approach mentioned earlier, AI and HI are supposed to work on the same task in parallel, and then their outputs can be aggregated. This approach is an emergent field that has just been opened up by the aforementioned study; as such, it has been less explored relative to its predecessors.

As the review of the literature revealed, a wide range of studies have focused on different approaches for teaming up between AI and HI in the form of augmented intelligence. Furthermore, this review shows that the literature has two specific gaps that the current study will attempt to fill. The first gap comes from the lack of attention to the interconnections between the nature of tasks and the desired setting for AI and HI collaboration. As discussed above, although the significance of such linkages has been articulated in the literature, attributes that define the nature of tasks and how these attributes can affect the suitable approach for teaming up AI and HI are still vague. The second identified gap is concerned with the context in which this literature is concentrated. The review shows that the predominant concentration of studies lies in augmented intelligence in the context of decision-making. Although decision-making is an organisational function associated with great opportunities to utilise augmented intelligence, it is not the only organisational function where augmented intelligence can be employed. It means any other area where HI plays a critical role can be a potential candidate for studying collaboration between AI and HI. One of these areas that deserves further attention is innovation practices. These practices not only have traditionally been dominated by HI but also are the organisations' growth engines where any small improvement can yield significant benefits.

### 3.2.3. Knowledge-based View of the Firm

As an extension to the Resource-based View (RBV) of the firm, the Knowledge-based View (KBV) of the firm emerged as a reconceptualised concept that examines firms by going beyond viewing them as mere possessors and processors of resources to treating them as entities whose core resource for value creation is knowledge, and any value creation effort is strongly associated with two knowledge-related activities, knowledge creation and knowledge utilisation (Grant, 1996; Kogut and Zander, 1992; Spender, 1996). In this context, Grant's (1996) foundational contribution established a fundamental principle rooted in Simon's concept of bounded rationality: "Fundamental to Simon's principle of bounded rationality is recognition that the human brain has limited capacity to acquire, store and process knowledge. The result is that efficiency in knowledge production (by which I mean the creation of new knowledge, the acquisition of existing knowledge, and storage of knowledge) requires that individuals specialize in particular areas of knowledge. This implies that experts are (almost) invariably specialists, while jacks-of-all-trades are masters-of-none" (Grant, 1996, p. 112). This assertion demonstrates that given the bounded rationality that human individuals have, knowledge creation, encompassing all the steps that ultimately result in increasing organisational knowledge stock (i.e. knowledge acquiring, knowledge sharing, and learning by doing), significantly depends on specialised individuals whose knowledge is deeply narrowed to specific scope and domain.

Although knowledge creation requires specialists, what plays a crucial role in knowledge utilisation is diversity (Grant, 2013). In other words, introducing this specialisation principle creates the necessity of integrating and coordinating different types of specialised knowledge distributed amongst individuals, which Grant (1996) identified as one of the main challenges for organisations. Introducing such a view on knowledge shifted the focus from viewing it as a static resource to a dynamic entity that relies on sophisticated coordination mechanisms. Grant's (2013) later reflections emphasise that "knowledge-based approaches to understanding organizations have shifted attention from the traditional emphasis on coordination of activities to coordination of knowledge" (Grant, 2013, p. 542), which highlights the importance of knowledge coordination efforts. In a similar work, Kogut and Zander (1992) demonstrated that organisations gain competitive advantage through their superior performance in transferring and recombining knowledge in an effective way, compared with market mechanisms, rather than the mere ownership of valuable knowledge. Beyond the coordination challenge, individual specialists with specialised knowledge creates a cooperation problem as another challenge on which KBV particularly focuses (Grant, 1996).

In the realm of the KBV theory, one of the fundamental assumptions is that humans play the primary role as the sole organisational agents in knowledge creation and utilisation processes (Grant, 1996; Nonaka and Takeuchi, 1995). This perspective emphasises the crucial role of individuals in knowledge-related activities, as argued by Nonaka (1994). This centrality of humans' role, particularly regarding tacit knowledge, was evident in Polanyi's (1962) conception of tacit knowledge as "we can know more than we can tell". This implies that tacit knowledge is deeply rooted in human creation and values, which makes it difficult to formalise and transfer, but it provides a strong foundation for innovative insight and creative problem solving (Nonaka and Takeuchi, 1995). Having such a view on human agency across the knowledge-intensive organisations not only introduces humans as the only types of organisational specialists but also demonstrates that the coordination and cooperation challenges all stem from when these bounded rational specialists work together. However, when AI is adopted by knowledge-intensive organisations, aforementioned setting is not the only possible situation. Indeed, such organisations by incorporating AI, as a digital technology that while can automate processes is able to simultaneously work with humans, faced with a context where two types of intelligent agents, AI and HI, can collaborate and work together. This collaboration can reshape innovation practices by altering knowledge creation and utilisation processes through the joint agency of AI and HI. While this transformation can alleviate some of the issues around cooperation and coordination rooted in bounded rationality, it can also introduce new challenges in these areas previously unobserved, and potentially extends the KBV theory to accommodate non-human intelligence as a new category of specialist. In this regard, this study aims to understand how such a collaboration between AI and HI can be managed, by answering the following research question: *how can augmented intelligence be managed in the innovation practices of knowledge-based organisations?*

### 3.3. Methodology

Due to the novelty of the research question in this study and the lack of theory around it, a multiple-case study, theory-building approach, was used to find robust empirical evidence (Eisenhardt, 1989; Eisenhardt et al., 2016). Focusing on multiple cases rather than only one case is beneficial as it increases not only the reliability of gathered data but also enables cross-analysis, which may provide further novel insights (Yin, 2009). Managerial and organisational studies that focus on AI-related topics (i.e., augmented intelligence) are strongly associated with an abductive approach because of the contextual essence of AI (Von Krogh, 2018). In such a context, studying multiple cases would be more beneficial because adopting this approach can increase the generalisation power of research findings significantly.

### 3.3.1. Data Collection

Regarding the type of cases chosen, the current study is particularly focused on the knowledge-intensive sector. In this sector, innovation capacity and resulting competitive advantages have always relied heavily on HI embedded in organisations. Therefore, in the current era, when AI has been introduced as a novel type of non-human intelligence, studying collaboration between HI and AI in the form of augmented intelligence deserves more attention in this sector. Inspired by the research question on innovation practices, knowledge-intensive start-ups were chosen as sources of empirical data. Compared to established organisations, innovation practices are more vital for new-born start-ups because of the fierce competition they face. As a result, any evidence from such cases can yield more insight to address the research question.

Our sample consists of five knowledge-intensive start-ups. As a knowledge-intensive start-up, each of these chosen cases shares common characteristics, which is the significant HI's contribution in creation and utilisation of knowledge. However, these cases are purposefully chosen from diverse industries, namely the healthcare and well-being industry (n=3), advertisement and content creation industry (n=1), and software industry (n=1), where HI plays its critical role in different settings. Such a case design is necessary to increase the generalisability of the emergent theory (Eisenhardt, 2021). To gather the required empirical data from these cases, key informants with various roles, spanning founders and co-founders, technical leads, and business specialists, were invited for in-depth interviews. Furthermore, as part of data triangulation, to increase the validity and reliability of the gathered data (Yin, 2009), documents and reports about the chosen cases were analysed. In total, 31 individuals from the five cases were interviewed. The average time for each interview was 45 minutes. The summary information about the cases, including the interviewees' anonymised names and their corresponding roles are presented in Table 3. As shown in the Table, for start-up A, start-up B, start-up C, and start-up E, some of the interviewees are the same. These four start-ups are funded with the same mutual venture capital that provides funding, and required technical and business support for their operations. As a result, the technical and business staff of this venture capital were interviewed as another group of key informants. Each of these venture capital's staff members were interviewed for each case individually.

Table 3. Participant information

| Start-up name | Anonymised name of interviewee | Role |
|---|---|---|
| **Start-up A** | Interviewee A1 | Co-founder |
| | Interviewee A2 | Technical lead |
| | Interviewee A3 | Co-founder |
| | Interviewee F | Business staff |
| | Interviewee I | Business staff |
| | Interviewee M | Technical staff |
| | Interviewee L | Business staff |
| | Interviewee P | Business staff |
| **Start-up B** | Interviewee B1 | Co-founder |
| | Interviewee F | Business staff |
| | Interviewee I | Business staff |
| | Interviewee M | Technical staff |
| | Interviewee L | Business staff |
| | Interviewee P | Business staff |
| **Start-up C** | Interviewee C1 | Founder-CEO |
| | Interviewee C2 | Technical lead |
| | Interviewee C3 | Business development manager |
| | Interviewee C4 | Business staff |
| **Start-up D** | Interviewee D1 | Founder-CEO |
| | Interviewee D2 | Technical lead |
| | Interviewee F | Business staff |
| | Interviewee I | Business staff |
| | Interviewee M | Technical staff |
| | Interviewee L | Business staff |
| | Interviewee P | Business staff |
| **Start-up E** | Interviewee E1 | Founder-CEO |
| | Interviewee E2 | Technical lead |
| | Interviewee F | Business staff |

| | |
|---|---|
| Interviewee I | Business staff |
| Interviewee M | Technical staff |
| Interviewee L | Business staff |
| Interviewee P | Business staff |

The first case chosen from the healthcare and well-being industry, start-up A, operates in the field of remote patient monitoring enabled by AI. This start-up designed services that can determine the patient observations (e.g., pulse rate, respiration rate, and oxygen saturation) as easily as taking a photo. What this start-up offers allows general practitioners and individual patients to better understand vital signs (i.e., heart rate, blood oxygen level, and breathing rate) using only a smartphone camera. These services are based on sophisticated AI algorithms capable of working with huge volumes of data. Additionally, by designing related Application Programming Interfaces (APIs), these offerings can be integrated with other digital healthcare solutions, such as those provided by telemedicine providers.

The second case studied from the healthcare and well-being industry, start-up B, focuses on providing AI-based solutions powered by visual data processing technology. This start-up enhances the processes of sports and healthcare service providers, such as gyms and physiotherapists. Their AI-based solutions enable trainers and physiotherapists to gain more accurate insights into the current physiological conditions of their trainees and patients, respectively. Additionally, these experts are provided with complementary solutions to help their clients improve their physiological conditions or recover from physical injuries.

The third case studied from the healthcare and well-being industry, start-up C, operates in the psychiatric field. This start-up is a spinoff of a well-established psychiatric clinic that was founded 20 years ago. With high-quality and rich data accumulated from two decades of work in this field, the clinic was able to design a robust AI-powered system capable of diagnosing psychiatric disorders (e.g., bipolar disorder, anxiety, depression) in a systematic way, rather than relying on lengthy patient interviews. Additionally, this AI-based system can provide psychiatrists with information about possible treatments and the required dosages of medication for diagnosed disorders.

The studied case from the advertisement and content creation industry, start-up D, is a content provider. This start-up generates professional content in the Farsi language for a wide range of audiences, including copywriters, content teams of digital platforms, marketing agencies, influencers, and non-professional users who want to create written work on a particular topic. Like popular large language model (LLM) service providers, this start-up generates content based on prompts received from its users to meet their specific needs. Additionally, this start-up offers auditing services to enhance any written content and make it more professional, depending on the requested context.

The last studied case, start-up E, is from the software development industry. This start-up designs smart chatbots and virtual advisors powered by large language models (LLMs) in the Farsi language. Depending on their target market, they aim to automate mundane and repetitive tasks typically performed by front-line service workers, such as those in customer service. In other words, what this start-up is focused on is designing smart agents that can do a range of mundane tasks, particularly across the areas where there is a sufficient amount of well-documented text data (i.e. customer call centres and law firms).

### 3.3.2. Data Analysis

The analysis process mostly depended on primary data gathered through in-depth and semi-structured interviews with key informants of the chosen cases. For data triangulation, several sources for each case were utilised, mostly archival online data from the cases' websites and professional social media accounts (namely, LinkedIn and X). These data provided more contextual insights about the nature of the operations that each case has.

In the first step of the analysis, a within-case analysis was conducted. During this phase, each case was analysed individually. This within-case analysis is a useful approach that enables researchers to become deeply familiar with the chosen case, considering the large volume of data that can be collected for each case (Eisenhardt, 2021). This process is indeed helpful for effectively exploiting the collected data to gain robust insights with the highest resolution about the studied cases and how they operate, in line with the research scope and research questions for which these cases were chosen. Given the diversity of interviewed key informants and their perspectives on each case, the recorded data from the interviews were used as the primary source for the within-case analysis. The recorded audios were listened to and analysed multiple times to gain a detailed understanding of each case. For within-case analysis, inspired by work carried out by Braun and Clarke (2006), thematic analysis was utilised. In this regard, each case was treated individually. First, interview scripts from each case were analysed and reviewed multiple times. Then, the initial codes were generated from these scripts. Finally, through an iterative process, final themes were developed for each studied case. Consistent with others (Eisenhardt, 1989; Hannah and Eisenhardt, 2018; Bremner and Eisenhardt, 2022), the synthesis of these resulting insights developed a detailed description of how each of the selected cases operates by yielding insights into the problems and the needs of customers targeted by these cases to address, the available solutions to address these problems, the role of HI in the problem-solving process in the situation where there is not any AI, the nature of areas where AI can be used to solve these problems differently, HI's and AI's distinct contribution towards problem-solving process when they are both utilised together in the form of augmented intelligence, and the resulting innovation when AI is introduced alongside HI in providing solutions for customers' needs and problems.

To avoid over-reliance on information from individual cases, which may cause significant biases, to find novel patterns embedded in the collected data, and to increase the generalisation power of emergent findings, a cross-case analysis was also carried out. To conduct this analysis, inspired by suggestions from Eisenhardt (1989) and Yin (2009) about analysing cases across different dimensions and categories, a range of relevant constructs were chosen. These constructs focus on the problems solved by studied cases and the AI-based solutions that these cases propose to solve these problems. Cases were then grouped according to their differences and similarities relative to each construct. The relevancy of these constructs was defined with respect to the problems and questions that this research attempts to address, related academic literature, insights and findings from within-case analysis, and the knowledge and expertise of the researchers in this study about the phenomenon being investigated.

The constructs used to categorise the chosen cases into distinct groups were the *type of problems* and the *transferability of solutions*. The cases within each group share similar characteristics along each dimension, while they are distinct and different from each other across different groups.

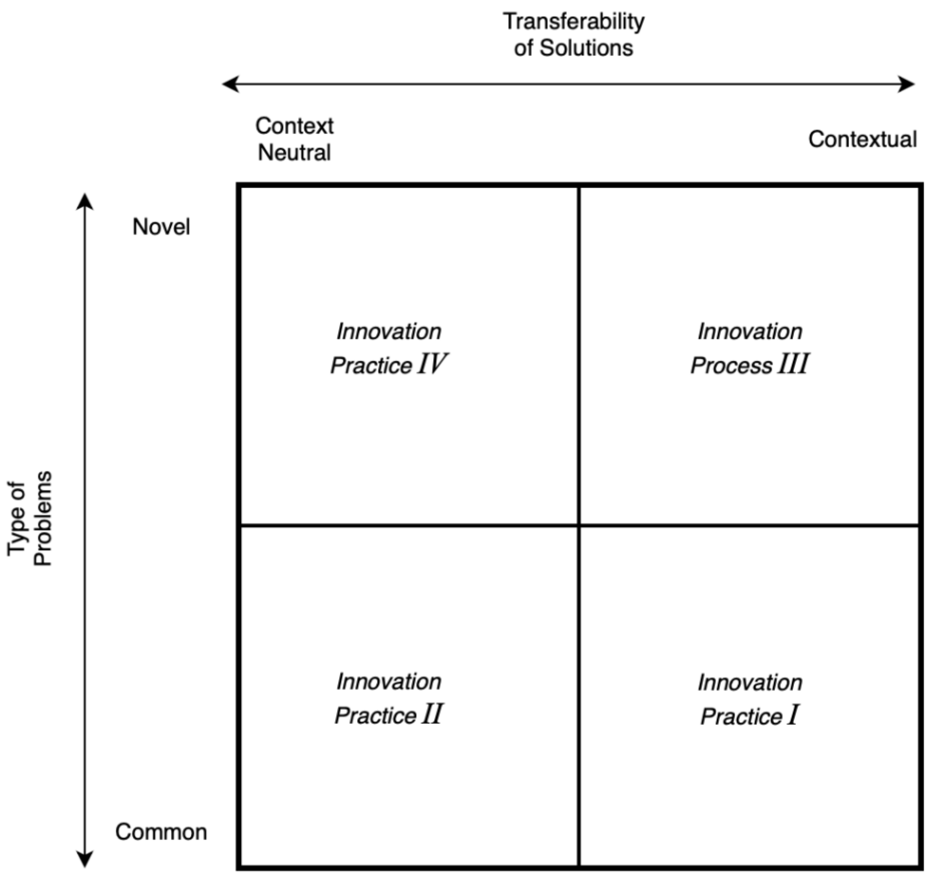
*Type of problems* is a construct that demonstrates the extent to which a problem solved by the knowledge-intensive start-up is novel. In this regard, the problems are divided into two different groups. While the first group consists of *common problems* that exist regardless of whether there are any AI-based solutions to solve them or not, the second group focuses on *novel problems* that could not have been imagined before introducing AI into the problem-solving process.

*Transferability of solutions* is a construct that defines the extent to which AI-based solutions provided by knowledge-intensive start-ups are context-neutral. In other words, this categorisation demonstrates whether new AI-based solutions for different problems, and thus innovation, are transferable from one context to another or not.

### 3.3.3 Developed Theoretical Framework

Based on the above-mentioned cross-case analysis and the interpretation and coding of each case's collected data, the following framework was designed (Figure 2). This framework identifies four unique pathways of innovation based on the type of problem targeted by organisations in knowledge-intensive sectors and the degree of dependency of their AI-based solutions on specific contexts. It also outlines the respective settings through which augmented intelligence can be managed.

Figure 2. Augmented Intelligence-enabled Innovation Practices




***Innovation Practice I***

This type of innovation practice is carried out by start-ups that deal with solving common problems that already exist. It means at this level, AI and its associated advantages cannot enable organisations to focus on novel types of problems that have not been considered before and AI's function is limited to providing new solutions for the existing problems to solve them in a better way. As depicted in Figure 1, the contributions that AI can make are contextual and non-transferable from one context to another one due to their massive focus on solving particular types of narrowed problems. Across the studied cases, only start-up A that focuses on providing healthcare services enabled by AI to determine vital signs adopted this type of innovation practices. In a situation where HI was the only source of intelligence, the diagnosis stage, including both determination and interpretation of the vital symptoms, was carried out by HI. However, by introducing AI the determination phase is delegated to AI. The assertion on such a task division between AI and HI is clearly evidenced by the insights that key informants from this start-up provided. For example, one of this start-up's co-founders said that "if we want to only focus on our product, we are part of the monitoring process in which we generate data. We are a data provider, and human is the consumer of these data" (Interviewee A1).

These insights reveal a particular type of setting implemented to manage augmented intelligence. According to this setting, AI is responsible for providing accurate data used by HI in the next decision-making steps, including diagnosis and prescription to cure a patient. This unique utilisation of AI alongside HI across the diagnosis process is the implemented innovation at this level. The output of this type of innovation is improved accessibility to healthcare solutions, particularly in remote control systems implemented for controlling and observing patients remotely. All the interviewees from this start-up reflected on such an innovative outcome. For example, a technical lead of this start-up mentioned that "the goal we had was to make remote controlling more accessible" (Interviewee A2). Another example is a statement from one of the co-founders of this start-up where he said "I believe that [our goal] at this stage is still accessibility. […] accessibility in most cases is translated into someone who has geographical limitations, means that his limitations are defined in terms of geography. In some areas financial issues are concerned, it means that you can categorise financial issues under the term of accessibility, […] Ultimately, we can consider all of these as something we can do to enable more people to have access to remote healthcare monitoring, regardless of the problem they may have" (Interviewee A3).

### *Innovation Practice II*

Similar to *the Innovation Practice I*, this type of innovation happens when organisations are supposed to solve the common problem and AI makes contributions towards providing better solutions compared to a situation where HI was the only player. However, unlike that discussed for the *Innovation Practice I*, proposed AI-based solutions at this level are transferable and context neutral. This means that AI-based solutions designed and utilised by start-ups whose innovation practices are categorised under this type of innovation can be used and adopted in a new context with only minor justifications.

Across the cases studied, start-up B can be grouped into this category of innovation practices. As mentioned earlier, this start-up is focused on empowering trainers and physiotherapists to have a better understanding of their clients' physiological status and issues by utilisation of AI-based solutions. In terms of the context neutrality aspects of these solutions, it is worth noting that start-up B is now able to utilise its AI-empowered solutions in new contexts which are different, compared to the initial context of their operation, such as in analysing football matches.

Findings from this case revealed a unique augmentation setting for collaboration between AI and HI where AI's role and function are not solely limited to a determination tool. According to this setting, AI provides accurate data with some degree of analysis, which can be considered as a rough diagnosis, and HI uses the analysed data for making the final decision about diagnosis and prescription. In other words, at this level, AI is supposed to provide HI with analysed and interpreted data rather than raw data. This is the distinguishable aspect of augmentation setting of this type of innovation compared to the *Innovation Practice I* where AI was only supposed to provide accurate raw data by acting as a measuring tool. The ability of AI in providing analysed data rather than raw data was mentioned by different key informants of start-up B. For example, one of the interviewees who is a board member of both start-up A and start-up B mentioned that "… start-up B can even make diagnosis. It seems that in its operation, diagnosis is the same as measuring. It does not know the reason for physical issue, but its scope is clearer [compared to start-up A]" (Interviewee F). This unique task division between AI and HI was evidenced by Interviewee I from this start-up where he said: "if some [physical] issues are spotted from the user, you can connect him/her to a doctor or physiotherapist, if these issues are more severe". As Interviewee I emphasised, the serious identified issues can be directed to the medical experts, which means that this start-up's AI-based solutions have some degree of ability to interpret the gathered data.

Similar to what was depicted for the first type of innovation practice, before utilisation of AI as a new source of intelligence, all of this process from diagnosis to prescription was carried out by HI. However, by introducing AI into the process, AI is now capable of carrying out some aspects of diagnosis by providing analysed data that are used by HI to complete the diagnosis and prescription phases. This unique augmentation setting to utilise AI and HI is the innovation carried out compared to a situation where HI was the key player and only responsible for the whole process from diagnosis to prescription. The outcome of this innovation is increased speed and accuracy of diagnosis. This outcome was clearly depicted by various key informants interviewed from this start-up, including a statement by the founder regarding their ultimate goal "what we look for is speed and accuracy for some non-aggressive approaches for diagnosis" (Interviewee B1). In another example from the technical staff of start-up B, this non-aggressive diagnosis was translated into lower costs for end users: "accuracy and cost reduction for the end user. I may use their mirror features to monitor my body status. If my body status is poor and I am likely to face a problem, I will address it soon and take it seriously" (Interviewee M). This increased accuracy was also mentioned by one of the board members of start-up B: "it decreases the workload. In a shorter time, it provides the same interpretation of the result. The second [priority] is accuracy […] Generally, in medical-related solutions, accuracy is important" (Interviewee F).

***Innovation Practice III***

The third type of innovation practice happens when organisations rather than dealing with common problems through working on improved solutions enabled by AI, by utilisation of AI, focus instead on solving novel problems that were not possible to be considered and worked on before introducing AI. Among the studied cases, this type of innovation practice was carried out by start-up C and start-up D, whose primary focus is on diagnosis and treatment of psychiatric disorders, and content generation in Farsi, respectively.

As shown in Figure 1, start-ups under this category can focus on novel problems that were not possible to be considered without AI. For start-up C, this novelty stems from the fact that, due to AI's capabilities in handling huge volume of data, this start-up can now work with unique data captured from brain circuits that were not interpretable before integrating AI into the process. For start-up D, the novelty of the targeted problems is rooted in the start-up's core operation, content generation, which was only doable by HI before emergence of Large Language Models (LLMs). However, despite the novelty of the problem that these start-ups aim to solve, as depicted in Figure 1, their solutions are narrowly focused on specific areas, and thus, are contextual and non-transferable. This contextual nature of the solutions was mentioned by a wide range of key informants from these two start-ups. For example, the technical lead of start-up D stated that "A given solution can be similar for different contexts more or less; our resources may be a bit different, but at the end of the day, it is about search, research, reading, understanding, and ultimately wrapping up. If the output of this process was not a particular solution, it was not possible to implement it as AI. From this perspective, [considering AI in the solution], it can be considered as the contextual solution" (Interviewee D2). The business development manager from start-up C made the following statement about the contextual-oriented solutions they provide: "although the process is unified, the diagnosis and prescription are different from one case to another" (Interviewee C3).

Findings from these cases revealed two specific settings to manage augmented intelligence. In start-up C, HI's main responsibility is to verify the diagnosis that AI makes about different psychiatric conditions that any individual case may have and to offer an individualised prescription and treatment plan based on the provided diagnosis by AI. This task division between AI and HI was emphasised by the founder and CEO of start-up C: "AI is still a student being taught and trained. However, it is a student whose ability is more than its teacher. Therefore, what should be considered across the contributions from these two is that I [need] to provide correct data, carry out enough observations on the work it does, till it can find its way and like any given student it becomes independent from its teacher" (Interviewee C1). Despite the similar role that HI plays in verifying the content generated by AI in start-up D, HI is also responsible for providing AI with the scope and the topic for which content should be created. In other words, in start-up D, HI first defines topic, scope, and requirements that AI should consider for generating content, and then, once AI generates this content, HI is responsible for verifying it against the set goals and making any required amendments. Performing such an observation role by HI was mentioned by different interviewees from this case. For example, Interviewee I mentioned that: "what is the next stage? Now HI comes to read the content. It means it must observe the generated content to check, is it correct?". Compared to the situation where HI was the only player, these unique settings for collaboration between HI and AI are the innovation practices implemented across these cases.

Findings from the interviewed key informants from these start-ups identified increased accuracy and speed as the outcome of such an innovation. These increased accuracy and speed were mentioned by various interviewed informants from these cases. For example, Interviewee I from start-up D said: "if someone from a content team who works for me, if he/she spends one hour on content creation, how can he/she make this, one hour, to 30-40 minutes? To first reduce the time [spent on content creation] , and second, increase its accuracy". In another quote from the founder of start-up D, these increased speed and accuracy were introduced as the enhanced efficiency, where he said: "the main problem is efficiency in content creating. This efficiency can be in the form of money-saving, time-saving and marginal cost. For example, if you want to create a particular content at 11 pm it is not possible to call someone. In the first step, you should set an agreement and contract which can take a few days. Finally, the degree to which that person is fit to your expectations. This is more about efficiency" (Interviewee D1). From a similar perspective, the founder and CEO of start-up C reflected on the importance of increased accuracy as he said: "at this stage, since we are at the beginning of the process, increasing the diagnostic accuracy is important for us and is helpful, but our primary priority could be providing an available, affordable, more effective, and more measurable caring solution, based on what we can achieve [based on our AI solutions]" (Interviewee C1).

***Innovation Practice IV***

Similar to what was discussed for the third type of innovation practice, at this level organisations are supposed to work on problems that were not possible to be imagined before introducing AI into the problem-solving process. However, unlike *innovation practice III*, any potential AI-based solutions proposed for these kinds of problems are not limited to a specific context and are able to be utilised across various contexts with required justifications. Start-up E from the software engineering industry whose focus is on designing AI-enabled smart chatbots and advisors, falls under this category. The novelty of the problem this start-up is focused on to solve, is rooted in designing intelligent agents that are not humans. Utilisation of advice from robots and smart advisors rather than humans is a phenomenon that, until relatively recently, was only possible in the imaginations of science-fiction stories. However, due to the capabilities associated with AI, this dream has become a reality. In terms of the transferability of the AI-based solutions, evidence from the key informants of this start-up reveal that their AI-enabled solutions can be adopted across a wide range of contexts, like customer services empowered by chatbots, smart assistants for web purchasing, and legal advisors, to name but a few. Furthermore, evidence from the interviews provided insights on the augmentation settings that are utilised to exploit AI and HI alongside each other. In this regard, the vast majority of the process is supposed to be carried out by AI, and HI is supposed to only have contributions towards unusual and exceptional cases. Taking customer service chatbots as examples, most of the customer enquiries and issues can be managed by chatbots and only specific needs that are exceptional may be referred to humans for further assistance. This approach is clearly depicted in a statement from the founder of this start-up E where he said: “we delegate all the repetitive tasks to AI and our [human] agents will be able to solve unique problems by spending more time and exploiting a capability they have in interpretation of emotional data” (Interviewee E1). In another statement from one of the financial experts from the investor team of this start-up it was mentioned that: “if the work is not done, this is a stage where that AI or chatbot should be connected to the human operator” (Interviewee I).

Findings from interviews with key informants suggested that the outcome of such an innovation practice through the collaboration between AI and HI is increased reliability of provided solutions to clients. This is due to the lower rate of errors associated with AI’s performance rather than HI when the workload is increased. This outcome was reflected by various informants from this case. For example, Interviewee I by considering the call centre as the representative context of this solution mentioned that: “how I can either reduce the number of call centre’s staff or increase their efficiency, by increasing their speed, accuracy and decreasing their error rate”. In another reflection on this outcome, Interviewee L said that “start-up E wants to reduce the organisation’s needs for call centre’s staff, addressing the frequent and repetitive questions […], this can decrease the staff number and increase the quality of answering which means it can lead humans faster to their [required] answers”. Such reduction in the above needs can ultimately lead to more reliable solutions through less intervention of humans on repetitive tasks whose performance is associated with more error once their workload is increased.

### 3.4. Discussion

Digital technologies have consistently opened new opportunities for organisations to be more innovative. Depending on the types of the key resources that organisations utilise to create, gain, and sustain competitive advantages, digital technologies can drive different types of innovation by altering these resources, their combinations, and utilisations. Among the various types of resources introduced from different perspectives and across multiple disciplines, knowledge is one of the most important. Considering knowledge as the primary source of competitive advantages and focusing on AI as one of the most crucial digital technologies that can enable a wide range of innovations, by studying five start-ups from knowledge-intensive sectors, this research proposes four unique pathways for innovation practices, which are AI-altered knowledge creation and utilisation processes.

*Research Implications*

Drawing upon the Knowledge-based View (KBV) of the firm, when knowledge is treated as the main source of competitive advantage, a given organisation's success in gaining and sustaining these advantages depends on the degree to which it has unique knowledge relative to others and/or utilises this knowledge in distinguishable ways compared to its competitors. Considering how knowledge functions as the primary resource in organisations, any innovation enabled by digital technologies is expected to impact knowledge creation and utilisation across the organisation. In such a context, it has always been assumed that humans are the sole source and consumer of knowledge, and thus, any technological innovation has traditionally aimed to empower humans in processes associated with knowledge creation and utilisation. However, by introducing AI as an agent capable of performing certain tasks better than humans and carrying out some functions that are not achievable by humans, HI may not be the only source of intelligence. Translation of this assertion into the organisational context, particularly when knowledge is considered as the primary source of competitive advantages, means that the creation and utilisation of knowledge are no longer limited to humans. We now have agents that can discover novel patterns and insights (knowledge creation) or apply them more effectively (knowledge utilisation). From this perspective, the current study contributes to the KBV theory by providing a distinct task division between AI and HI in creation and utilisation of different types of knowledge (i.e., explicit and tacit knowledge).

The first and the most convenient type of task division between AI and HI belongs to the context of *Innovation Practice I*. At this level, AI is responsible for the utilisation of explicit knowledge. However, utilisation of explicit knowledge by AI does not necessarily imply that this task is only performed by AI. Indeed, HI still has a critical role in the utilisation and also the creation of both explicit and tacit knowledge, while AI's role is only limited to utilisation of explicit knowledge.

In the second type of task division between AI and HI, similar to what was mentioned above, AI's role is only limited to the utilisation of explicit knowledge without any participation in the utilisation and creation of tacit knowledge. However, unlike the previous level, the output of this utilisation contributes to the utilisation and creation of explicit knowledge by HI. It means when AI utilises explicit knowledge, the output of this utilisation can be used by HI in both of its crucial roles in utilisation and creation of explicit knowledge. In other words, although AI has no direct role in the creation of explicit knowledge, its participation in the utilisation of explicit knowledge can affect HI's role in the utilisation and creation of explicit knowledge, while such an impact cannot be expected for the previous level (i.e. *Innovation Practice I*). In such a context, in addition to the contribution that HI has in the creation and utilisation of explicit knowledge, the creation and utilisation of tacit knowledge are only carried out by HI. The corresponding innovation type for this kind of task division is *Innovation Practice II.*

The third type of task division between AI and HI across the process of knowledge creation and utilisation is associated with *Innovation Practice III.* At this level, for the first time, AI contributes to the creation of explicit knowledge. This means AI not only utilises explicit knowledge but also participates in the creation of this type of knowledge. The output of this participation in explicit knowledge creation is shared with HI, which is then used by HI alongside its tacit knowledge. What is important to note here is that at this stage, unlike the earlier discussion in the context of *Innovation Practice I* and *Innovation Practice II,* the utilisation and creation of explicit knowledge are fully delegated to AI and HI is only responsible for the utilisation and creation of tacit knowledge. At this level (i.e. *Innovation Practices III*), the created explicit knowledge by AI can impact and empower how tacit knowledge is utilised by HI.

The last type of task division belongs to the context of *Innovation Practice IV.* In this context, similar to the previous level (i.e. *Innovation Practices III*), the utilisation and creation of explicit knowledge is delegated to AI and tacit knowledge's utilisation and creation are only done by HI. However, unlike the previous context mentioned above, the output of explicit knowledge creation by AI contributes not only to the utilisation of tacit knowledge by HI but also to the creation of tacit knowledge done by HI. At this level, although AI makes no direct contribution to the utilisation and the creation of tacit knowledge, its active role in the utilisation and creation of explicit knowledge can empower HI's role in the utilisation and creation of tacit knowledge. The following table (Table 4) provides a brief description of how tasks for the utilisation and creation of explicit and tacit knowledge are divided between AI and HI, regarding each of the identified innovation practices.

As depicted below in Table 4, this task division between AI and HI illustrates how augmented intelligence (i.e., collaboration between HI and AI) can be managed across innovation practices by assigning distinct roles to each. This task division shows that AI's role in knowledge specialisation operates along a spectrum of sophistication, evolving from a basic user of explicit knowledge to encompassing explicit-knowledge creation and ultimately empowering human specialisation in tacit knowledge-related activities. This progression constitutes a major theoretical contribution of this study to the KBV, by reconceptualising Grant's (1996) argument on knowledge specialisation in the context of augmented intelligence.

Grant (1996) argued that efficient knowledge production requires specialised individuals in specific areas of knowledge, owing to bounded-rationality constraints. The findings of this paper extend this principle by demonstrating that AI can function as a novel source of intelligence that enhances and complements knowledge specialists. In playing such a role, AI can address some of the cognitive limitations inherent in human bounded rationality. This has profound implications for the KBV: rather than viewing specialisation solely as a response to human bounded rationality, it reframes specialisation as a strategic design principle that leverages the strengths of AI and HI as two sources of organisational intelligence. This view highlights a shift from specialisation born of bounded rationality to specialisation born of augmented intelligence.

Grant (2013) argued that KBV's approaches to understanding organisations have shifted the focus from coordination of activities to coordination of knowledge. When AI functions as a novel source of intelligence capable of collaborating with HI in the form of augmented intelligence, this Grant's (2013) view takes on new dimension. Findings from this study reveal that, in such a context, coordination and cooperation mechanisms can be affected.

Traditional KBV literature has focused on coordination challenges arising from the necessity of integrating specialised knowledge held by human specialists. Findings from this study demonstrate that introducing AI into knowledge-related activities can alleviate these coordination challenges in multiple ways. First, AI can reduce the cognitive burden on human coordinators by functioning as a knowledge-integration platform and synthesising explicit knowledge from different sources. Second, AI facilitates more efficient knowledge transfer and integration by standardising knowledge formats and interfaces. Third, AI enables asynchronous knowledge coordination and maintains organisational memory by operating as a persistent knowledge repository. However, this study also demonstrates that AI can impose new coordination challenges. As AI-generated explicit knowledge is integrated with human tacit knowledge, novel coordination mechanisms may be needed that do not exist in traditional KBV frameworks. This suggests that current coordination mechanisms (e.g. rules and procedures, sequencing, and routines) should be supplemented with AI-specific coordination mechanisms.

The next theoretical implication of this study is about the cooperation dynamics addressed within the KBV theory. As Grant (1996) reports, reconciliation and subordination of disparate goals of organisational member cause the cooperation problems. In such a context, while AI can alleviate some of these traditional cooperation problems, can also introduce new ones.

In other words, since AI does not possess any personal goals that conflict with organisational objectives, its involvement in knowledge-related activities can eliminate a major source of cooperation challenges. Also, due to AI's ability to perform unbiased analysis, potential conflicts and issues rooted in different interpretations can be reduced. However, other novel types of cooperation challenges can be emerged by introducing AI, particularly as AI systems require training, monitoring, and validation, all which shape new forms of cooperative work that require different skills and mindsets than traditional human-human cooperation.

Finally the last theoretical contribution of this study is how it expands the boundary of working with tacit knowledge. As shown in below table, contrary to the long-standing discourse on the central role of HI in the creation and utilisation of tacit knowledge, this study demonstrates that while HI remains the key role, AI also contributes to tacit knowledge creation and utilisation by empowering HI in these processes. This argument makes a significant contribution to the KBV theory literature, as it implies that the crucial role of non-human players is no longer solely limited to explicit knowledge creation and utilisation, but now extends to tacit knowledge domains through their capacity to empower HI. This represents a form of knowledge amplification that was not possible in purely human knowledge systems.

Table 4. Task division between AI and HI

| Innovation type | AI's role | HI's role |
|---|---|---|
| ***Innovation Practice I*** | Utilisation of explicit knowledge | • Utilisation of explicit knowledge<br>• Creation of explicit knowledge<br>• Utilisation of tacit knowledge<br>• Creation of tacit knowledge |
| ***Innovation Practice II*** | Utilisation of explicit knowledge + empowering the utilisation and creation of explicit knowledge by HI | • Utilisation of explicit knowledge empowered by AI<br>• Creation of explicit knowledge empowered by AI<br>• Utilisation of tacit knowledge<br>• Creation of tacit knowledge |
| ***Innovation Practice III*** | • Utilisation of explicit knowledge<br>• Creation of explicit knowledge + empowering the utilisation of tacit knowledge by HI | • Utilisation of tacit knowledge empowered by AI<br>• Creation of tacit knowledge |
| ***Innovation Practice IV*** | • Utilisation of explicit knowledge<br>• Creation of explicit knowledge + empowering the utilisation of tacit knowledge by HI + empowering the creation of tacit knowledge by HI | • Utilisation of tacit knowledge empowered by AI<br>• Creation of tacit knowledge empowered by AI |

### *Practical Implications*

For knowledge-intensive start-ups, this framework provides actionable guidance for AI implementation by identifying which knowledge processes should be allocated to AI versus HI based on problem novelty and solution transferability. Rather than adopting trial-and-error approaches that waste resources and miss market opportunities, managers can strategically design AI-HI collaboration models that leverage AI's capabilities while preserving human expertise in tacit-knowledge domains. Start-ups can use these four innovation pathways to assess their AI readiness, optimise resource allocation between contextual versus transferable solutions, and build sustainable competitive advantage through systematic augmented intelligence practices. Established organisations can apply this framework to redesign existing workflows, determining whether to pursue solving the common problem in a more efficient manner (Innovation Practice I and II) or breakthrough innovations through novel problem-solving (Innovation Practice III and IV), while ensuring proper coordination mechanisms between AI explicit-knowledge processing and human tacit-knowledge creation to maximise both operational efficiency and innovation capacity.

### 3.5. Conclusion

Utilisation of AI alongside HI in the form of augmented intelligence, has great potential in transforming how organisations carry out their innovation practices and how they achieve competitive advantages. This study demonstrates how knowledge-intensive start-ups are capable of leveraging AI as a collaborative partner to enhance traditional knowledge creation and utilisation. By adopting augmented intelligence, organisations can exploit new avenues for innovation, and thus obtain a competitive position against their rivals. This study informs the design of a conceptual matrix that serves as a foundational framework to understand these novel innovation patterns and their corresponding settings to manage augmented intelligence, which offer valuable theoretical and practical insights for both established firms and emerging start-ups across knowledge-intensive sectors.

## References


Abadie, A., Roux, M., Chowdhury, S., & Dey, P. (2023) Interlinking organisational resources, AI adoption and omnichannel integration quality in Ghana's healthcare supply chain. *Journal of Business Research*, 162, 113866.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019) Exploring the impact of artificial intelligence: Prediction versus judgment. *Information Economics and Policy*, 47, 1-6.

Baird, A., & Maruping, L. M. (2021) The Next Generation of Research on IS Use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS Quarterly*, 45(1), 315-341.

Balasubramanian, N., Ye, Y., & Xu, M. (2022) Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review*, 47(3), 448-465.

Baptista, J., Stein, M.-K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020) Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *The Journal of Strategic Information Systems*, 29(2), 101618.

Barney, J. (1991) Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research. *Journal of the Association for Information Systems*, 22(2), 281–303.

Braun, V., & Clarke, V. (2006) Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77-101.

Bremner, R. P., & Eisenhardt, K. M. (2022) Organizing form, experimentation, and performance: Innovation in the nascent civilian drone industry. *Organization Science*, 33(4), 1645-1674.

Brynjolfsson, E., & Hitt, L. M. (1998) Beyond the productivity paradox. *Communications of the ACM*, 41(8), 49-55.

Brynjolfsson, E., & McAfee, A. (2017) The business of artificial intelligence. *Harvard Business Review*, 7(1), 1-2.

Chattaraman, V., Kwon, W. S., Ross, K., Sung, J., Alikhademi, K., Richardson, B., & Gilbert, J. E. (2024) 'Smart'Choice? Evaluating AI-Based mobile decision bots for in-store decision-making. *Journal of Business Research*, 183, 114801.

Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2023) Human-AI ensembles: When can they work?. *Journal of Management*, 51(2), 536-569.

Cook, S. D., & Brown, J. S. (1999) Bridging epistemologies: The generative dance between organizational knowledge and organizational knowing. *Organization Science*, 10(4), 381-400.

Csaszar, F. A., & Steinberger, T. (2022) Organizations as artificial intelligences: The use of artificial intelligence analogies in organization theory. *Academy of Management Annals*, 16(1), 1-37.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019a) Hybrid intelligence. *Business & Information Systems Engineering*, 61(5), 637-643.

Dellermann, D., Lipusch, N., Ebel, P., & Leimeister, J. M. (2019b) Design principles for a hybrid intelligence decision support system for business model validation. *Electronic Markets*, 29, 423-441.

Dicuonzo, G., Donofrio, F., Fusco, A., & Shini, M. (2023) Healthcare system: Moving forward with artificial intelligence. *Technovation*, 120, 102510.

Eisenhardt, K. M. (1989) Building theories from case study research. *Academy of Management Review*, 14(4), 532-550.

Eisenhardt, K. M. (2021) What is the Eisenhardt Method, really?. *Strategic Organization*, 19(1), 147-160.

Eisenhardt, K. M., Graebner, M. E., & Sonenshein, S. (2016) Grand challenges and inductive methods: Rigor without rigor mortis. *Academy of Management Journal*, 59(4), 1113-1123.

Eisenhardt, K. M., Santos, F. M., Pettigrew, I. A., Thomas, H., & Whittington, R. (2000) Knowledge based view. *Handbook of strategy and management.* London: Sage Publications.

Goodfellow, I., Bengio, Y., & Courville, A. (2016) *Deep learning* (1st ed). Cambridge, MA: MIT Press.

Grant, R. M. (1996) Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109-122.

Grant, R. M., & Baden-Fuller, C. (1995) A knowledge-based theory of inter-firm collaboration. *Academy of Management Proceedings*, 1995(1), 17-21.

Grant, R. M. (2013) Reflections on knowledge-based approaches to the organization of production. *Journal of Management & Governance*, 17(3), 541-558.

Gupta, A. K., & Govindarajan, V. (2000) Knowledge flows within multinational corporations. *Strategic Management Journal*, 21(4), 473-496.

Haenlein, M., & Kaplan, A. (2019) A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14.

Hannah, D. P., & Eisenhardt, K. M. (2018) How firms navigate cooperation and competition in nascent ecosystems. *Strategic Management Journal*, 39(12), 3163-3192.

Holzinger, A. (2016) Interactive machine learning for health informatics: When do we need the human-in-the-loop?. *Brain Informatics*, 3(2), 119-131.

Huysman, M. (2020). Information systems research on artificial intelligence and work: A commentary on "Robo-Apocalypse cancelled? Reframing the automation and future of work debate." *Journal of Information Technology*, 35(4), 307–309.

Issa, H., Jaber, J., & Lakkis, H. (2024) Navigating AI unpredictability: Exploring technostress in AI-powered healthcare systems. *Technological Forecasting and Social Change*, 202, 123311.

Jarrahi, M. H. (2018) Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.

Kogut, B., & Zander, U. (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, 3(3), 383-397.

Kordjamshidi, P., Roth, D., & Kersting, K. (2022) Declarative learning-based programming as an interface to AI systems. *Frontiers in Artificial Intelligence*, 5, 755361.

Murray, A., Rhymer, J. E. N., & Sirmon, D. G. (2021) Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, 46(3), 552-571.

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science*, 5(1), 14-37.

Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company : how Japanese companies create the dynamics of innovation. Oxford University Press.

Ostheimer, J., Chowdhury, S., & Iqbal, S. (2021) An alliance of humans and machines for machine learning: Hybrid intelligent systems and their design principles. *Technology in Society*, 66, 101647.

Pham, P., Zhang, H., Gao, W., & Zhu, X. (2024) Determinants and performance outcomes of artificial intelligence adoption: Evidence from US Hospitals. *Journal of Business Research*, 172, 114402.

Polanyi, M. (1962) *Personal Knowledge - Towards a Post-Critical Philosophy*. London: Routledge and Kegan Paul.

Raisch, S., & Krakowski, S. (2021) Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192-210.

Rodgers, W., Hudson, R., & Economou, F. (2023) Modelling credit and investment decisions based on AI algorithmic behavioral pathways. *Technological Forecasting and Social Change*, 191, 122471.

Schulz, M. (2001) The uncertain relevance of newness: Organizational learning and knowledge flows. *Academy of Management Journal*, 44(4), 661-681.

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020) Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, 57(2), 103174.

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019) Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 61(4), 66-83.

Simon, H. A. (1955) A behavioral model of rational choice. *The Quarterly Journal of Economics*, 99-118.

Singha, S., Arha, H., & Kar, A. K. (2023) Healthcare analytics: A techno-functional perspective. *Technological Forecasting and Social Change*, 197, 122908.

Song, C. S., & Kim, Y. K. (2022) The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *Journal of Business Research*, 146, 489-503.

Spender, J. C. (1992) Limits to learning from the West: How Western management advice may prove limited in Eastern Europe. *The International Executive*, 34(5), 389-413.

Spender, J. C. (1996) Making knowledge the basis of a dynamic theory of the firm. *Strategic Management Journal*, 17(S2), 45-62.

Spring, M., Faulconbridge, J., & Sarwar, A. (2022) How information technology automates and augments processes: Insights from Artificial-Intelligence-based systems in professional service operations. *Journal of Operations Management*, 68(6-7), 592-618.

Stelmaszak, M., Möhlmann, M., & Sørensen, C. (2025) When Algorithms Delegate to Humans: Exploring Human-Algorithm Interaction at Uber. *MIS Quarterly*, 49(1), 305–330.

Sveiby, K. E. (2001) A knowledge-based theory of the firm to guide in strategy formulation. *Journal of Intellectual Capital*, 2(4), 344-358.

Teece, D. J. (1986) Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6), 285-305.

Teece, D. J. (2010) Business models, business strategy and innovation. *Long Range Planning*, 43(2-3), 172-194.

Tsoukas, H. (1996) The firm as a distributed knowledge system: A constructionist approach. *Strategic Management Journal*, 17(S2), 11-25.

Upadhyay, N., & Kamble, A. (2024) Why can't we help but love mobile banking chatbots? Perspective of stimulus-organism-response. *Journal of Financial Services Marketing*, 29(3), 855-872.

Vellido, A. (2020) The importance of interpretability and visualization in machine learning for applications in medicine and health care. *Neural Computing and Applications*, 32(24), 18069-18083.

Von Krogh, G. (2018) Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, 4(4), 404-409.

Weick, K. E., & Roberts, K. H. (1993) Collective mind in organizations: Heedful interrelating on flight decks. *Administrative Science Quarterly*, 38(3), 357-381.

Yin, R. K. (2009) *Case study research: Design and methods* (Vol. 5). Beverly Hills, California: Sage.

Zhu, H., Vigren, O., & Söderberg, I. L. (2024) Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda. *Journal of Business Research*, 174, 114494.

Zott, C., & Amit, R. (2010) Business model design: An activity system perspective. *Long Range Planning*, 43(2-3), 216-226.

# Chapter 4: Generative artificial intelligence in higher education: the ecosystem perspective

**Shayan Rashidi**

**Abstract**

This study explores the transformative impact of Generative Artificial Intelligence (Gen AI) on the higher education ecosystem, focusing on the case of Lancaster University Management School (LUMS) as a knowledge-based institution. Drawing on the ecosystem-as-structure perspective, the research investigates how Gen AI affects the value propositions offered by the higher education ecosystem. Adopting a qualitative research method, the study uniquely gathered empirical evidence by examining academicians' perspectives on Gen AI's role in knowledge creation and dissemination. The findings reveal a nuanced landscape where Gen AI acts as a novel ecosystem player, augmenting certain activities while simultaneously presenting challenges, particularly for student learning. By providing insights into the multilateral interactions between Gen AI and various actors in the higher education ecosystem, this research contributes to the emerging literature on ecosystems, Gen AI in the context of higher education, and educational innovation.

Keywords: Generative Artificial Intelligence, Higher education, Ecosystem

## 4.1. Introduction

The public release of ChatGPT by OpenAI in November 2022 marked a tremendous shift in how AI models work and function, a wave referred to as Generative AI (Gen AI) (Roumeliotis and Tselikas, 2023). Indeed, for the first time since the AI concept was born during the Dartmouth Conference in 1956, by introducing Gen AI, sophisticated AI algorithms have become available to people as easily as typing a message on a mobile phone. Departing from the early AI systems that were designed to perform narrow and specific tasks by harnessing a huge volume of data (Brynjolfsson and McAfee, 2017), these generative models, through being trained on extensive data sets and by utilising Large Language Models (LLMs), can generate human-like content across a wide range of areas (Stokel-Walker, 2023). Compared to their predecessors, these models can adjust their outputs based on the inputs from the user (i.e. prompt), a feature that provides them with significant levels of adaptability (Susnjak and McIntosh, 2024). Such an advantage has unlocked a wide range of opportunities, particularly in areas like knowledge-based institutions, where human expertise has traditionally made a crucial contribution.

Borrowing from the Knowledge-based View of the firm (KBV), a knowledge-based institution is defined as an entity whose core asset is knowledge, utilised for creating value, either through creating knowledge or utilising knowledge, regardless of whether they are operating for profit or not (Nonaka and Takeuchi, 1995; Grant, 1996; Spender, 1996; Eisenhardt et al., 2000). From this perspective, universities as entities comprising a highly skilled workforce whose primary focus is creating knowledge through research and disseminating knowledge through educating people are appropriate representations of knowledge-based institutions (Rowley, 2000; Bano and Taylor, 2015; Adeinat and Abdulfatah, 2019). The significant dependency of these kinds of institutions on human expertise makes them suitable candidates to embrace Gen AI. Indeed, the unique capabilities associated with Gen AI have paved the way through which the major actors of this context (i.e. academicians and students) can play their roles in novel manners that had not been imaginable before (Kung et al., 2023; Kulkarni et al., 2024). This impact implies how advancements in Gen AI are reshaping the higher education landscape, and challenging the established ways through which universities create and deliver their value propositions. However, despite the significant implications of Gen AI for the higher education sector, whilst much attention has been given to its technical and ethical implications, less is understood about its systemic effects on the structures and processes that underpin value creation in higher education. Furthermore, the current literature on Gen AI and the higher education sector is predominantly characterised by a speculative and descriptive orientation rather than theoretically grounded inquiry (Brown et al., 2024). To adequately address this problem, there is a need to move beyond traditional, firm-centric theoretical models and adopt an ecosystem perspective that captures the multilateral interdependencies among the diverse actors involved in higher education. In this regard, the current study, by adopting the ecosystem-as-structure (Adner, 2017) perspective and gathering empirical data, aims to fill this gap by addressing the following research question: How can Gen AI affect the proposed value of a knowledge-based institution's ecosystem?

The rest of the paper is structured as follows. First, the corresponding literature on Gen AI in the context of the higher education sector, and the ecosystem perspective that serves as the theoretical lens of the current study, are discussed. Next, the employed research method is presented by providing details on data collection and data analysis. Finally, the paper demonstrates how Gen AI affects the proposed value of a knowledge-based organisation's ecosystem, along with the discussion of this study's contributions.

## 4.2. Literature Review

### 4.2.1 Gen AI in the higher education sector

Introducing Gen AI and its recent advances in generating human-like content has reshaped the higher education sector and universities significantly (Wang et al., 2023; Mollick and Mollick, 2023). Considering that higher education service providers, such as universities, are primarily focused on both knowledge creation (i.e. research activities) and knowledge dissemination (i.e. teaching and engagement activities), this context presents substantial opportunities to embrace Gen AI across the above-mentioned domains (Altbach, 2011; Henderson et al., 2024). In alignment with the current study's focus on impact of Gen AI on the values proposed by higher education service providers, findings from the corresponding literature revealed three main streams of research.

The first group of studies focuses on factors that can influence the adoption of Gen AI by universities (Gao et al., 2024; Budhathoki et al., 2024; Zhao et al., 2024). These studies are particularly concerned with influencing factors from the end-user's perspective. In a study done by Gao et al. (2024), examining ChatGPT, they found that the extent to which the generated outcomes by Gen AI are perceived as human-like by users affects its adoption. This study revealed the concerns that Gen AI users have about receiving answers and content that are similar to what is generated and produced by humans. In another group of studies, the anxiety level of Gen AI users (Budhathoki et al., 2024), and their cultural background (Zhao et al., 2024) were found to be other types of influencing factors for the adoption of Gen AI by the higher education sector.

The second stream of literature on studying Gen AI in the context of universities is more concerned with the potential consequences that integrating Gen AI into this area may have (Barros et al., 2023; Grimes et al., 2023; Krammer, 2023; O'Dea, 2024; Larson et al., 2024; Essien et al., 2024; Butler and Spoelstra, 2025). These studies reported a wide range of benefits and risks associated with the adoption of Gen AI by universities. These findings were about both teaching and research activities performed in higher education. Enhanced teaching methods and research equity (Barros et al., 2023; O'Dea, 2024), improved knowledge synthesis and increased research rigour (Grimes et al., 2023), personalised learning and improved assessment (Krammer, 2023), and increased efficiency in developing teaching materials (Larson et al., 2024) were among the identified positive impacts of Gen AI's integration into higher education. However, these studies found that the resulting benefits can be achieved at the cost of threats and challenges that Gen AI can pose to the higher education sector. In this regard, a wide range of negative impacts, including negative impacts on academic integrity and raised ethical issues (Grimes et al., 2023; Barros et al., 2023; O'Dea, 2024), decreased research quality, and deskilling of academics (Barros et al., 2023), providing false and fake information due to AI hallucinations (Grimes et al., 2023), increasing the chance of cheating by learners (Krammer, 2023), and eroding and demolishing reflexive learning and critical thinking (Larson et al., 2024; Butler and Spoelstra, 2025) were reported by this group of studies.

The last group of studies from the literature on Gen AI in the context of universities focused on the approaches that can be adopted to utilise Gen AI. In this regard, in a work done by Yang et al. (2024), two specific approaches for using Gen AI by students were reported. While the first approach focuses on passive learning, where the generated content by Gen AI is directly used by the students, the latter one considers a more proactive role for learners through evaluating and auditing Gen AI's output before incorporating them into the learning journey. In a similar study conducted by Nguyen et al. (2024), such approaches for using Gen AI in research activities were identified. According to the findings from this study, the interaction between AI and humans and their collaboration in the writing process could be more beneficial, compared to the situation where Gen AI is only used as a supplementary tool.

### 4.2.2 Ecosystem-as-structure

Ecosystem, despite its etymological roots in biological sciences, has emerged as a dominant phenomenon in strategic management, focusing on interactions between organisations whose activities depend on each other (Jacobides et al., 2018). In other words, this concept deals with how different groups of autonomous but interdependent players can work together to meet goals that satisfy all of them (Baldwin and Clark, 2000; Adner, 2006; Teece, 2018; Jacobides et al., 2018). Despite a clear agreement on what an ecosystem is focused on, a wide range of definitions have been proposed for this concept. Indeed, depending on the unit of analysis, different perspectives can be adopted to define an ecosystem. However, this is not a venue that the current study wants to compete in by providing another view to define an ecosystem. Instead, the current study looks for the most appropriate definition and perspective that can be adopted as a theoretical lens that informs data-gathering and analysis processes.

Within this broad literature, this study adopts the ecosystem-as-structure perspective, articulated most comprehensively by Adner (2017). This perspective provides an actionable theoretical framework for analysing how value is created and sustained through multilateral alignment among diverse sets of actors. Unlike the more actor-centric view, ecosystem-as-affiliation, which focuses on who is in the ecosystem, the ecosystem-as-structure approach starts with the constellation of activities required for the realisation of the ecosystem's value proposition.

According to Adner (2017), an ecosystem is defined as *"the alignment structure of the multilateral set of partners that need to interact in order for a focal value proposition to materialize."* This definition demands attention to four key structural elements:

*Activities*: the required interdependent actions to materialise the value propositions offered by any given ecosystem. In the context of higher education, these activities manifest as research, teaching, and engagement.

*Actors*: the entities who are responsible for undertaking the activities of the given ecosystem. In the higher education ecosystem, this set of actors consists of academic staff, students, administrative staff, and external partners (e.g. policy makers, businesses, government, other universities).

*Positions*: this element focuses on where actors are located across the activities required to materialise the proposed value of any given ecosystem and ultimately defines who hands off to whom. For example, in the higher education ecosystem, module conveners are positioned as the creators and distributors of knowledge to educators and students.

*Links*: the shared transfers between actors across the activities they take part in. Taking teaching as an example activity in the higher education ecosystem, links may take the form of curriculum delivery and students' feedback.

Central to this framework, value propositions play a crucial role by forming the endogenous boundary of the ecosystem. This centrality indicates that value propositions serve as distinguishing features that define the functionality of a given ecosystem, with ultimate impacts on the types of structural elements previously mentioned (i.e. activities, actors, positions, and links). In other words, the ecosystem-as-structure approach, with its particular emphasis on the proposed value offered by ecosystems and the underlying activities required for the realisation of these propositions, offers a comprehensive theoretical lens that has informed this study's data gathering and analysis to address the research question: how can AI affect the proposed value of a knowledge-based institution's ecosystem?

### 4.3. Methods

According to the research question, *How can Gen AI affect the proposed value of a knowledge-based institution's ecosystem?*, the current research is primarily focused on studying a phenomenon by answering the *how* question. In this regard, the qualitative research method, as an approach that yields better insights into *why* and *how* questions, was chosen as the appropriate method to find rich and in-depth evidence to answer the research question (Lune and Berg, 2017; Yin, 2009).

#### 4.3.1 Data collection

Drawing upon the chosen theoretical lens (i.e. ecosystem-as-structure), the creation of the proposed value of a given ecosystem depends on the activities carried out by the actors whose multilateral relationships shape this ecosystem. Adopting such a theoretical perspective fits perfectly with the context of the current study. This is because, on the one hand, universities offer clear value propositions, like research and education. On the other hand, the materialisation and creation of these values depend on the activities of a wide range of autonomous actors whose activities are substantially interconnected through multilateral relationships and shared resources.

In such a context, academic workforce, as highly skilled knowledge workers, is among the crucial players whose contributions play a critical role in the required activities for the creation of value propositions offered by universities. Having such an influential role in knowledge-related activities (i.e. knowledge creation and knowledge utilisation), which are at the core of any knowledge-based institution, makes this group of actors an appropriate candidate to embrace Gen AI. In this regard, to find out how Gen AI can affect the proposed values of knowledge-based institutions' ecosystems (i.e. universities), this research studied this phenomenon from the academic workforce's point of view. In this regard, considering the higher education sector as a representative area of the knowledge-based sector, Lancaster University Management School (LUMS) was chosen as a case study.

To gather the required empirical evidence for this study, 22 academic staff from LUMS were recruited as research participants. As discussed earlier, the distinguishable character of knowledge-based institutions is their primary focus on knowledge as the core asset, knowledge creation, and knowledge utilisation (Nonaka and Takeuchi, 1995; Grant, 1996; Eisenhardt et al., 2000). From this perspective and in the context of universities, the creation and utilisation of knowledge heavily depend on academic staff as highly professional knowledge workers. In this regard, interviewing these staff enabled this study to find reliable first-hand empirical evidence from actors' points of view who make a significant contribution towards the underlying activities required to materialise their respective ecosystem's value propositions. Alongside a particular enquiry line inspired by the adopted theoretical lens, open-ended questions were asked from the interviewees due to the proven functionality of this method in providing participants with enough flexibility in reflecting on their novel insights (Yin, 2009). Interviews were all conducted via Microsoft Teams in compliance with the ethics application approved by Lancaster University's Faculty of Arts and Social Science (FASS) and Management School (LUMS) Research Ethics Committee. The transcripts of the interviews were generated by the embedded auto-transcription tool within Microsoft Teams and were carefully reviewed and audited to correct typos and errors.

Interviewees were recruited from different departments, including Entrepreneurship and Strategy (ENST) (n=10), Management Science (n=5), Organisation, Work, and Technology (OWT) (n=4), and Marketing (n=3). Each interview was divided into two phases. In the first phase, participants were asked to identify the proposed value of LUMS as a knowledge-based institution from their perspective. They were then invited to explain and provide detailed accounts of the activities in which they had participated to create these proposed values. In the second phase, participants were asked how the introduction of Gen AI had affected the previously discussed value propositions and the underlying activities involved in creating them. Table 5 presents the summary information about the interviewees, including their anonymised names, corresponding departments, and roles.

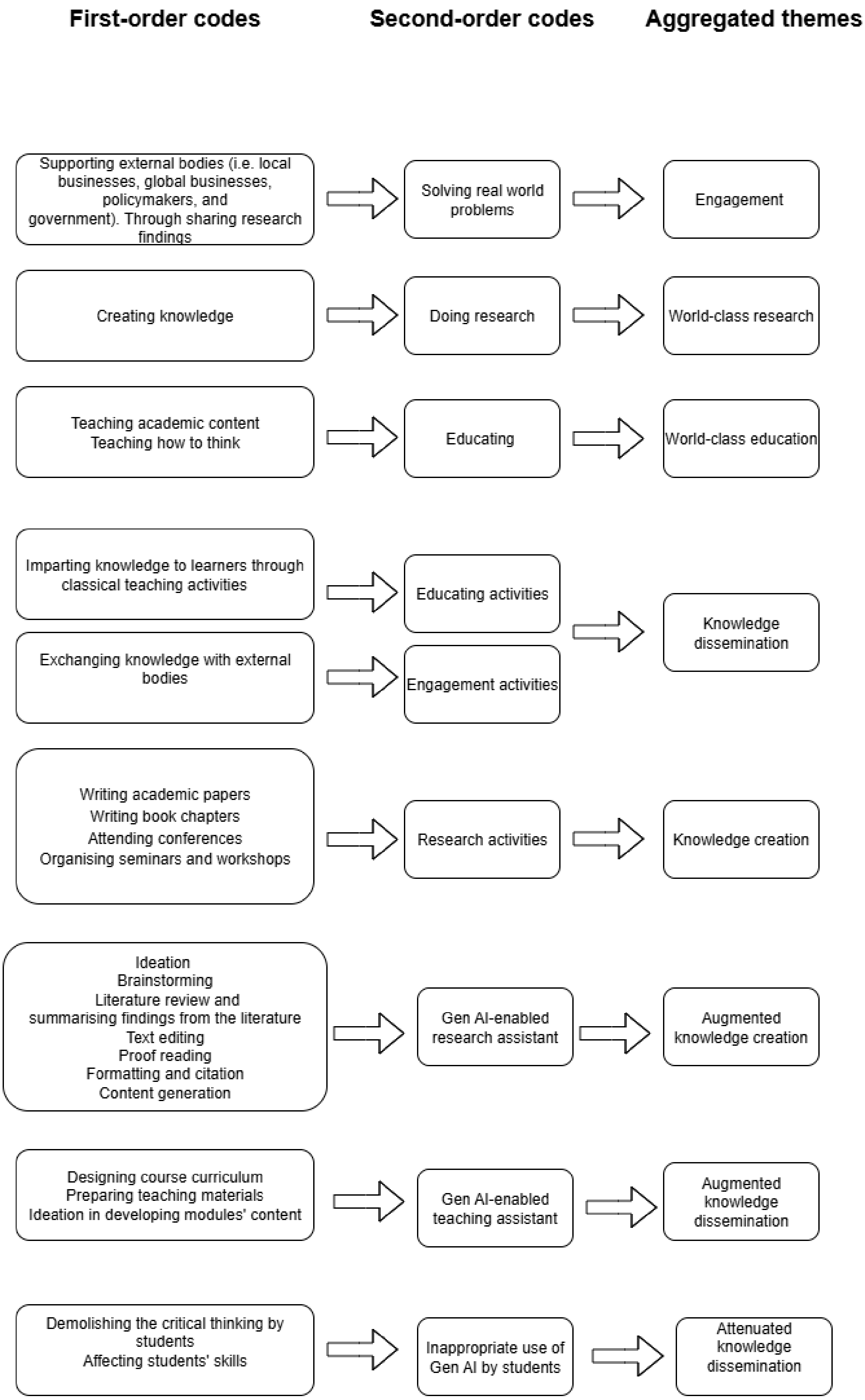
Table 5. Participants information

| Department name | Anonymised name of interviewees | Role |
|---|---|---|
| **Entrepreneurship and Strategy Department** | Interviewee B | Lecturer |
| | Interviewee E | Senior lecturer |
| | Interviewee F | Senior lecturer |
| | Interviewee I | Senior teaching fellow |
| | Interviewee J | Senior lecturer |
| | Interviewee N | Senior teaching fellow |
| | Interviewee M | Senior teaching fellow |
| | Interviewee O | Teaching fellow |
| | Interviewee R | Professor |
| | Interviewee T | Teaching associate, honorary teaching fellow |
| **Management Science Department** | Interviewee A | Professor |
| | Interviewee G | Lecturer |
| | Interviewee K | Lecturer |
| | Interviewee P | Professor |
| | Interviewee U | Lecturer |
| **Organisation, Work, and Technology Department** | Interviewee C | Senior lecturer |
| | Interviewee D | Senior teaching fellow |
| | Interviewee Q | Lecturer |
| | Interviewee V | Senior lecturer |
| **Marketing Department** | Interviewee L | Lecturer |
| | Interviewee S | Lecturer |
| | Interviewee H | Teaching fellow |

#### 4.3.2. Data Analysis

To answer the designed research question, inspired by a thematic analysis method introduced by Braun and Clarke (2006), the interview transcripts were analysed as the primary data source. In this regard, these transcripts were reviewed and analysed a minimum of 4 times each. Next, consistent with the chosen theoretical lens, ecosystem-as-structure, the smallest units of content that could inform the answer to the designed research question were extracted as the first-order codes. Then, according to the similarity of these codes, they were grouped into the more generic second-order codes. Finally, by aggregating these second-order codes, the final themes were developed. For example, regarding the activities carried out to create the proposed values of the studied case, knowledge creation was one of the emerging final themes, whose second-order and first-order codes were research, and writing academic papers, writing book chapters, attending conferences, and organising seminars and workshops, respectively. The summary of the first-order and second-order codes and their corresponding final themes are mentioned in Figure 3.

Figure 3. Data structure



### 4.4. Findings

Inspired by the chosen theoretical lens (i.e. ecosystem-as-structure), findings from the analysis of gathered data were used to demonstrate the proposed values of LUMS (i.e. education, research, and engagement), activities to create these value propositions (i.e. knowledge creation and knowledge dissemination), and finally the impact of Gen AI on these activities and value propositions.

#### 4.4.1. Value propositions

Regarding LUMS' value propositions, findings from the interviews revealed three specific groups of value propositions offered by LUMS, entitled education, research, and engagement. These value propositions were mentioned by almost all interviewees.

*World-class education*

Teaching and educating are among the primary focus areas of LUMS, as a higher education services provider. A senior teaching fellow from the ENST department highlighted LUMS' commitment to providing high-quality education by stating, "the second one we have is to ask potential students and our current students and that is to provide a transforming education that will transform their life chances, their knowledge, their skills, their ability to get jobs they want to get" (Interviewee I). This high-quality education is not merely limited to delivering academic concepts. Indeed, alongside teaching academic concepts, teaching students how to think critically and providing them with practical insights required for the job market are the other aspects of the education offerings of LUMS. A wide range of interviewees clearly mentioned this broad scope of teaching activities. Regarding enabling students to think critically, a senior teaching fellow from the OWT department said "… us teaching them how to think, not what to think, importantly, but developing their thinking skills" (Interviewee D).

In another similar quote, a senior lecturer from the ENST department said that "… we have a strong pedagogy around critical thinking, critical reflection" (Interviewee J). Regarding educating students and learners with practical insights rather than merely teaching them academic concepts, a lecturer from the Marketing department clearly depicted the importance of this area, as he said "I think there's the link that we make between theory and practice. That is often seen as being quite beneficial…" (Interviewee S).

*World- class research*

Findings from the interviews demonstrate that doing world-class research is one of the other LUMS' value propositions. Regarding this value, LUMS, as a research-intensive management school, is particularly focused on conducting high-quality research across different disciplines of the management field. The significant focus of LUMS on this value proposition was mentioned by almost all the interviewees. The importance of doing world-class research in LUMS' agenda was clearly mentioned in a quote from an ENST department professor as he said "… they do put a lot of emphasis on the research culture and do want prospective students and students to know they are being educated by, you know, world-class researchers as well" (Interviewee R). In another quote from one of the other ENST department faculty members, a senior lecturer reflected on how research is crucial for LUMS. She said that "One is in relation to our research, when we are clearly a research-intensive institution and we see ourselves at the forefront of creating knowledge in that capacity…" (Interviewee J). In a similar quote, a senior lecturer from the Management Science department said that "… there is also the other one, which is also important, the research, so it is more about writing papers and trying to find answers to some academic questions" (Interviewee P).

As findings demonstrate, doing impactful and high-quality research is an inevitable part of LUMS' identity, specifically across the areas where LUMS has traditionally made a significant contribution. Indeed, doing research in these areas is one of the distinguishable characteristics of LUMS that was referred to in a quote from a senior teaching fellow of the ENST department as he said "Certain specialties which make us maybe a little bit different from the next university down the road, which seems to be, you know, there's things we get awards for and things that we have a strong history in, for instance within the management school, systems thinking, as I'll just take one example or operational research or others…" (Interviewee M).

*Engagement*

The last value proposition of LUMS identified across the gathered data was engagement. As mentioned earlier, LUMS is a research-oriented management school whose focus is on carrying out impactful research. This means that the research produced by LUMS should be able to solve real-world problems. In this regard, findings from the interviews revealed that LUMS attempts to be engaged with external bodies (i.e. local businesses, global businesses, policymakers, and government) and share its research findings and expertise with others. Similar to the earlier mentioned proposed values, education and research, this value was also mentioned by almost all the interviewees.

The importance of this engagement was appropriately mentioned by a professor from the Management Science department, who is particularly engaged in knowledge exchange activities with external bodies for sharing research findings. He said that “what stakeholders do we have? we have local businesses, we have global businesses or local organisations, global organisations. We have the government, we have the students…, I mean what we could, I mean the classic one is, do a lot of local business support, organisational support. We do this in pockets” (Interviewee A). The commitment of LUMS to be engaged with businesses and external stakeholders was also mentioned by a senior lecturer from the ENST department. He said that “So every time we have an interaction, there is an opportunity to create a knowledge transaction and therefore to create knowledge and at the same time create value for different individuals” (Interviewee F).

### 4.4.2. Activities

The creation of the aforementioned value propositions depends on a range of activities. In this section, the activities performed by interviewed academic staff members from LUMS are explained. According to the findings and consistent with the KBV view on the main activities of knowledge-based organisations, two groups of activities, named knowledge creation and knowledge dissemination, are required to create and materialise the introduced value propositions.

*Knowledge creation*

As mentioned earlier, LUMS is a research-intensive higher education service provider, and one of its value propositions is *world-class research.* In this context, *knowledge creation* was identified as one of the major activities carried out by LUMS academic staff to materialise their research-oriented value propositions. The role of academic staff who participate in these activities is *knowledge creator.* According to the findings from the gathered and analysed data, *knowledge creation* is substantially linked with creating new knowledge through doing research-related activities, like writing academic papers, writing book chapters, attending conferences, and organising seminars and workshops.

The importance of this type of activity for creating the LUMS’ research-associated value propositions was clearly mentioned by a wide range of interviewees. For example, a senior lecturer from the ENST department said that “Carrying out research activities really. So you [are] basically interested in as an academic, you're basically doing research, so that would involve the whole sort of set of activities that are involved [in]. Conducting research activities. Also attending conferences, you know, like organising seminars, and all these kind of things" (Interviewee E). In another quote from a senior lecturer from the ENST department, this research essence of *knowledge creation* was emphasised. She said "OK, so in relation to research, obviously I am a researcher, so I publish journal articles in top journals. I've also written a couple of textbooks and I've another book coming out next month" (Interviewee J).

*Knowledge dissemination*

*Knowledge dissemination* is another aspect of activities carried out by LUMS academic staff to create its value propositions. As the title of this group of activities demonstrates, knowledge dissemination deals with exchanging and disseminating knowledge, and thus, the role of academicians who take part in this group of activities is *knowledge disseminator*. In this context, the disseminated knowledge is what was created through the *knowledge creation* activities. According to the findings from the gathered data, this activity is particularly associated with two of LUMS' value propositions, *world-class education* and *engagement*. This means that the created knowledge is disseminated either through educating learners or engaging with external stakeholders (i.e. local businesses, global businesses, policymakers, government). While knowledge dissemination through education-related activities is more concerned with imparting knowledge to students through classic teaching activities, knowledge dissemination through engagement activities deals with sharing the outputs of knowledge creation activities with external bodies and enabling them to apply these findings. These findings were substantially evidenced by a wide range of interviewees. About the educational aspects of *knowledge dissemination,* a senior teaching fellow from the ENST department clearly reflected on different activities carried out by him, as he said "… I'm on a teaching contract. That means then that the way I design, develop and deliver a curriculum from the very idea to create a module and then convene it as a module convener to pull other academics around me and the professional services team in moving from design to development and then to engage" (Interviewee M).

Although the created knowledge from *knowledge creation* shapes a significant part of what is disseminated through the *knowledge dissemination*, this disseminated knowledge is not necessarily all about academic knowledge. This was emphasised and mentioned in a quote from a senior teaching fellow from the OWT department, as he said "So that ramming knowledge into students' heads, it's not about getting them to memorise stuff, you know, to memorise, say, theories or some, I don't know, facts and figures or whatever else; it's all about getting them to think about the complexity that is involved" (Interviewee D). In a similar quote from an honorary teaching fellow from the ENST department, imparting practical knowledge was mentioned, as he said "… so for me it's about maybe disseminating experiential knowledge and to some extent skills that have been acquired over time in the business arena" (Interviewee T).

The second aspect of *knowledge dissemination* is particularly associated with another value proposition offered by LUMS (i.e. *engagement*). In this regard, LUMS academic staff are substantially involved in *knowledge dissemination* activities through exchanging their knowledge and expertise with external stakeholders. In this context, similar to what was discussed earlier for educational aspects of *knowledge dissemination*, the knowledge that is exchanged here is the knowledge produced through *knowledge creation*, complemented with the domain expertise of LUMS academic staff members. This aspect of *knowledge dissemination* was mentioned by a wide range of interviewees, particularly those who are involved in engagement activities with external stakeholders. As an example, a senior lecturer from the Management Science department said that "The second direction that I do is working with companies. I do a little bit of consultancy…, so we sometimes have contacts with companies, and they get in touch with us, and they want to understand whether they do things correctly or not" (Interviewee P). In a similar quote, a professor from the Management Science department shared his insights about the engagement activities he usually takes part in. He said "…for small businesses, I should offer you knowledge seminar. For the global businesses, I should develop targeted relationships and again have focused workshops with them to showcase and help them to apply the research that we're doing" (Interviewee A).

A noteworthy aspect of these engagement activities is that LUMS not only provides insights and knowledge to external bodies but also learns from them. In other words, during the knowledge exchange process, external players also share knowledge. This knowledge can inform LUMS academic staff in their other activities, including educational aspects of *knowledge dissemination* and *knowledge creation.* This bilateral direction for knowledge exchange and dissemination was clearly mentioned by a senior lecturer from the ENST department, as he said "… when we have that engagement with businesses that actually do all this, we are trying to extract all the different bits of information about all these different transactions, all these different dynamics and understand them, analysing and create insights for them that can really be used for students who are interested in doing something like this, who are interested in going to work with these organisations and therefore interested to go into work for that" (Interviewee F). This fascinating fact was evidenced in another quote from a teaching fellow from the ENST department, where she reflected on her engagement with local businesses, "I have some engagement with our small businesses, but again, not normally in the educational setting of me teaching them and passing my knowledge on to them. It is normally utilising them to enhance what knowledge I can share with my students" (Interviewee O).

#### 4.4.3. Impact of Gen AI

Findings from the gathered data revealed that introducing Gen AI into the higher education context has affected the value proposed by this ecosystem in two directions. While the first direction is associated with positive impacts, the latter is about negative consequences. In this regard, the positive direction consists of augmented knowledge creation and augmented knowledge dissemination, and the negative direction comprises attenuated knowledge dissemination.

*Augmented knowledge creation*

As mentioned earlier, Gen AI's distinguishable character is its ability to understand and produce human-like content. Having this unique feature has made Gen AI a popular technology among LUMS' knowledge creators, whose primary focus is creating knowledge through doing high-quality research activities. In this regard, findings from the analysed data demonstrated that Gen AI augments LUMS' knowledge creators by serving them as a research assistant in their knowledge creation activities.

Regarding the *augmented knowledge creation* enabled by Gen AI as a research assistant, interviewees reflected on two different phases where Gen AI contributes. While the first phase is more focused on preliminary steps of doing research, (e.g. ideation, brainstorming, literature review and summarising findings from the literature), the second phase consists of steps associated with writing a paper (e.g. text editing, proofreading, formatting and citation, and content generation). Utilisation of Gen AI across the aforementioned areas was substantially mentioned by a wide range of interviewees, specifically academic staff involved in research activities. As an example, a professor from the Management Science department said, "If I want to know about a topic, I don't know, what are the five things that organisations could benefit from to create innovation? I, in the first instance, just to broaden my mind, I put this question to ChatGPT…" (Interviewee A). In another similar quote, a lecturer from the ENST department shared her insights about using Gen AI for text formatting purposes, as she said "It would have taken a lot more [time] to manually do the citation and things like that for me, so more time consuming. Now it is helping me to kind of do it in a shorter time…" (Interviewee B).

*Augmented knowledge dissemination*

According to the findings from the analysed data, the second direction where Gen AI can affect the proposed values of LUMS as a knowledge-based institution is *augmented knowledge dissemination*. As mentioned earlier, the *knowledge dissemination* activities that LUMS academic staff are involved in comprise two types: those associated with providing education offerings to learners, and those focused on knowledge exchange with external stakeholders, such as businesses and government. However, findings about *augmented knowledge dissemination* showed that only those kinds of activities linked with educational aspects of *knowledge dissemination* have been affected by Gen AI. In other words, Gen AI directly impacts the educational aspects of *knowledge dissemination* activities, but since in the engagement aspects of *knowledge dissemination,* the created knowledge from the *knowledge creation* activities is shared with external players, it can be said that Gen AI affects the engagement aspects of *knowledge dissemination* activities indirectly.

Similar to what was discussed for *augmented knowledge creation*, *augmented knowledge dissemination* benefits from the assistance role that Gen AI plays. In this context, Gen AI assists *knowledge disseminators* in designing the course curriculum and preparing the teaching materials for the modules that they work on. In this regard, Gen AI can be either used for ideation purposes or generating content related to course materials. Evidence about this aspect of Gen AI's utilisation in the context of *knowledge dissemination* was clearly mentioned by interviewees, particularly those more focused on teaching activities (i.e. teaching fellows). As an example, a senior teaching fellow from the ENST department appropriately reflected on how Gen AI has been integrated into all his teaching activities, as he said "… I discussed you kind of the brief flow of design, development, delivery, and I use, I personally use then as it, you know, [in] designing a module, I use it in the design phase, I use it in the development phase. I use Gen AI anyhow from the first weeks it was developed" (Interviewee M). In another quote, a lecturer from the Management Science department reflected on the rooms that exit for adoption of Gen AI into her teaching activities. She said "… there are certain things that you can generate using it more efficiently. For example, you can generate images and graphs, videos to make your classroom more engaging” (Interviewee G).

Regarding how Gen AI can be used for ideation purposes within teaching activities, a professor from the Management Science department said “I will use this quite heavily also when I'm developing the module content. Again, just for creativity, sometimes ChatGPT is very good in giving the three strongest bullet points for something that saves me a significant amount of time. The good thing is I have the expertise to judge which they give me 10 bullet points. I know the three. These are the three strongest. I consider myself to be knowledgeable enough to make a judgement what is good and what is not good, but it would take me a long time on my own to come up with these ten bullet points” (Interviewee A).

*Attenuated knowledge dissemination*

As mentioned earlier, causing positive impacts is not the only direction through which Gen AI affects LUMS' value propositions and underlying activities to create these value propositions. Indeed, findings from the gathered data introduced *attenuated knowledge dissemination* as the negative impact that Gen AI has on educational aspects of *knowledge dissemination* activities. According to these findings, while using Gen AI by *knowledge creators* and *knowledge disseminators* has augmented the activities they undertake (i.e., *knowledge creation* and *knowledge dissemination*), using Gen AI by students and learners is associated with destructive impacts.

Although this study was carried out from the academic staff members’ point of view, there are obviously other types of actors involved in the higher education ecosystem. Indeed, findings from the interviews reported a wide range of other actors, such as professional and career service teams, students, entrepreneurs in residence, local businesses, global businesses, and administrative staff members. Notably, among various actor groups, students were the only ones mentioned by interviewees as the actors whose contributions have been affected by Gen AI. Given students' active involvement in their learning journey through assessments and projects, their over-reliance on Gen AI for assignments and learning practices was identified as a destructive impact, entitled *attenuated knowledge dissemination*.

As mentioned earlier, one of the LUMS’ value propositions is *world-class education*. Regarding this value proposition, the importance of critical thinking was substantially emphasised by interviewees. In such a context, *attenuated knowledge dissemination* implies how Gen AI causes a negative influence on educational aspects of *knowledge dissemination* through demolishing critical thinking skills among the learners and students. This issue was evidenced by a wide range of interviewees. For example, a senior teaching fellow from the OWT department said “the purpose of writing an essay, even to create a bit of copy, you know, a readable piece of text, it's about thinking, you know, thinking about the arguments, doing all the research, weighing the, you know, all the scientific arguments, and then you just write it down. If you don't go through the process, if you get AI to do it for you, then you've missed out on a valuable opportunity” (Interviewee D). In a similar quote, a lecturer from the Marketing department shared his perspective about the negative impacts of Gen AI on thinking, where he said, “So I wouldn't say at all that it's all positive. I would say there are lots of negatives to it, I think, and arguably it deskills people because you don't have to think so much because a large language model does it for you, because it's not really AI as such, it's actually just a large language model” (Interviewee S).

### 4.5. Discussion

Findings from the current study contributed to the understanding of how Gen AI can be integrated into the higher education ecosystem and affect the value propositions offered by this ecosystem. In this regard, the following theoretical and practical implications can be introduced.

*Theoretical implications*

The first theoretical contribution of this study is examining the higher education sector from an ecosystem perspective. To the best of my knowledge, this is the first attempt to study a non-profit institution like a university through the lens of an ecosystem perspective, which emerged from a particular focus on competition. By adopting an ecosystem-as-structure perspective, LUMS was selected as the case study. The findings provide a rich picture of the higher education ecosystem’s value propositions (i.e. world-class education, world-class research, and engagement), the required activities performed by academic staff to create these value propositions (i.e. knowledge creation and knowledge dissemination), and the roles this academic workforce plays in these activities (i.e. knowledge creator and knowledge disseminator). Extending the ecosystem-as-structure perspective beyond its traditional for-profit domains to encompass non-profit knowledge-based institutions, the current study expands the boundary conditions of ecosystem theory and ultimately demonstrates the perspective’s analytical versatility across diverse institutional contexts.

The second theoretical contribution of this study lies in its reconceptualisation of technology as an active ecosystem actor, thereby advancing ecosystem literature in strategic management. As an emerging stream of knowledge in strategic management, ecosystem research primarily focuses on multilateral interactions between actors whose activities are interdependent. Among different perspectives that have studied ecosystems, ecosystem-as-structure, as the chosen theoretical lens of this study, is particularly concerned with the activities required for creating an ecosystem's value propositions.

These foundational activities to create an ecosystem's value propositions must be performed by a specific set of actors, which can vary depending on the ecosystem's nature. In this regard, when a higher education institution like LUMS and its surrounding ecosystem are studied, these actors typically include academic staff members, students, administrative staff members, businesses, policymakers, government, and other universities. Adner's (2017) ecosystem-as-structure perspective introduces activities, actors, positions, and links as the core structural elements of ecosystems. While this perspective and its broader ecosystem literature have conceptualised actors predominantly as human individuals or organisational entities, empirical evidence from the present study challenges and extends this traditional view.

This study makes a foundational contribution towards ecosystem theory, in general, and the ecosystem-as-structure perspective, in particular, by reconceptualising technology (i.e. Gen AI) not as a mere and passive instrument, but as an active ecosystem actor with distinctive capabilities, positioning, and relational dynamics in the realm of the ecosystem-as-structure concept. Empirical findings demonstrate that Gen AI functions as a novel type of actor characterised by assistive agency. This conceptualisation, unlike fully autonomous agency, which implies independent decision making and goal-setting capabilities, describes a form of collaborative participation wherein Gen AI augments human actors' capabilities in *knowledge creation* and *knowledge dissemination* activities without fully substituting human agency. This view recognises that Gen AI is actively involved in underlying activities for the creation of the value propositions offered by the higher education ecosystem by taking on specific positions within the activity structure (as research assistant and teaching assistant) and establishing novel links with human actors. While viewing technology as a crucial ecosystem component is not necessarily a novel concept, the emergence of a technology-enabled actor like Gen AI that actively and collaboratively participates in the ecosystem's core value-creating activities, rather than merely facilitating coordination or information exchange, represents a significant contribution towards ecosystem studies literature. This contribution by introducing a new category of actor with an intermediary position between passive technological infrastructure and fully autonomous human or organisational actors extends the ecosystem-as-structure theory, and thereby enriches the current understanding of how diverse forms of agency shape ecosystem dynamics.

The third theoretical contribution addresses the activity-level ecosystem reconfiguration prompted by the introduction of technology-enabled actors. The ecosystem-as-structure perspective adopts an activity-centric approach to the ecosystem with a particular focus on interdependent activities required to materialise the value propositions offered by the ecosystem. Building upon this foundation, this study introduces the reconfiguration in the ecosystem's activities, defined as the fundamental shift in the modality of required activities to realise the value propositions offered by the ecosystem.

Current ecosystem literature has examined various forms of ecosystem change, such as emergence, evolution, and disruption. However, it has not systematically addressed how the introduction of a technology-enabled actor (i.e. Gen AI) with assistive agency prompts adjustments to the underlying activities that constitute an ecosystem's foundation. Findings from this study reveal that when Gen AI is introduced as an active actor into the higher education ecosystem, the modality of both *knowledge creation* and *knowledge dissemination* activities undergoes fundamental changes. For academic staff acting as *knowledge creators* and *knowledge disseminators*, Gen AI's assistive participation enables augmented performance of their activities, which represents a positive activity-level reconfiguration. However, findings also demonstrate a more problematic dimension of activity-level ecosystem reconfiguration, when students start to use Gen AI to bypass rather than augment essential learning activities. This utilisation of Gen AI by students, who are other actors within the higher education ecosystem, undermines the educational value proposition of the higher education ecosystem. This attenuation represents a negative activity-level reconfiguration as the modality of student learning activities is shifted, which ultimately compromises the fundamental purpose those activities were designed to serve (e.g. critical thinking and deep learning capabilities). This dual nature of activity-level reconfiguration illustrates a crucial theoretical insight. In this regard, this study demonstrates that the introduction of technology-enabled actors does not produce uniform effects across an ecosystem. This finding represents a novel theoretical contribution to the ecosystem-as-structure perspective, demonstrating that ecosystem reconfigurations can be simultaneously beneficial and detrimental within the same system, contingent upon actor positioning, activity type, and the nature of interaction between human and technology-enabled actors. These contributions advance ecosystem-as-structure and its broader literature to address the contemporary age of AI, providing a robust conceptual foundation for understanding how AI reshapes value-creating ecosystems across diverse contexts.

*Practical implications*

Drawing on the theoretical contributions and empirical findings of this study, this section introduces detailed practical and policy implications for three primary groups of stakeholders: higher education institutional leaders and managers, policymakers and regulators, and technology providers. These implications demonstrate how findings from this study provide actionable guidance to enhance the value propositions offered by knowledge-based institutions in the age of Gen AI.

The first practical implications of this study are tailored to higher education institutional leaders and managers. According to findings from this study, this group of stakeholders needs to develop differentiated AI governance frameworks that recognise Gen AI's dual role as both an augmenting and a potentially attenuating technology. To address the paradox revealed by this study about Gen AI’s impacts on the value propositions offered by higher education ecosystems, university leaders and managers should establish cross-functional AI governance committees comprising representatives from information technology, academic affairs, student services, legal compliance, and faculty bodies to oversee AI initiatives and ensure alignment with institutional values. Moreover, to cope with challenges of attenuated knowledge dissemination, higher education service providers need to redesign their assessment strategies in a way that preserves opportunities for critical thinking development while acknowledging Gen AI's availability. Such a revision in assessment strategies plays a crucial role in appropriate usage of Gen AI with lower risk.

Alongside the aforementioned actions, findings from this study can help higher education service providers to train students in a manner that they can use Gen AI constructively. In this regard, universities must establish mandatory training courses that explicitly teach students to harness Gen AI as an augmentation tool, similar to how academic staff use it, rather than an automation substitute. These programmes should deliver structured modules encompassing rigorous methodologies for critically evaluating Gen AI outputs, systematic identification of algorithmic limitations and biases, and clear distinctions between pedagogically sound augmentation and academically problematic automation. Furthermore, as students proceed with learning how to use Gen AI within their learning journey, academic staff also require professional development in learning how to use Gen AI in their tasks efficiently and responsibly. As this study revealed, academic staff may be able to use Gen AI either in their teaching-related activities or in their research endeavours. In this regard, preparing them for the appropriate usage of Gen AI while academic staff's higher-order intellectual skills are preserved and enhanced is crucial to ensure that Gen AI's advantages are utilised appropriately by these knowledge workers.

The second practical implication of this study provides insights for technology firms seeking to integrate AI-based solutions into the higher education ecosystem. As this study revealed, when Gen AI is viewed as an augmenting technology, it can enhance the underlying activities required to create the value propositions offered by the higher education ecosystem and ultimately improve these value propositions. However, when Gen AI is viewed as a technology to automate all the steps, its impact is more destructive. These findings offer interesting themes for further investigation by tech firms, suggesting a strategic approach to designing AI solutions that align with and support—rather than replace—the unique value propositions of higher education institutions. This finding implies that technology firms should design educational AI solutions with built-in constraints that require human insight, critical thinking, and intellectual contributions. These features should foster brainstorming, creative thinking, editing, and refinement, while preventing full automation of intellectually-intensive tasks. In practice, this means that proposed AI solutions should be equipped with feedback-oriented rather than completion-oriented features, which provide suggestions, questions, and critiques rather than generating complete text that students can submit without intellectual engagement. Moreover, these features create a condition in which solutions produced by Gen AI require sophisticated, context-specific prompts that necessitate domain knowledge, preventing passive usage patterns.

To ensure Gen AI solutions make constructive and positive contributions to the value propositions offered by higher education service providers, technology firms should establish partnerships with universities. These types of collaborations enable technology providers to co-design AI solutions that, while addressing the real educational and research needs of universities, preserve their core value propositions. These collaborations should involve relevant stakeholders and users (e.g. academic staff and students) to ensure AI-based solutions support learning goals rather than undermining them. An effective partnership approach can include co-design workshops that allow academic staff and students to be involved in regular sessions, where AI features are refined in an iterative process to align with pedagogical objectives. This collaboration can also be complemented by providing comprehensive educational resources that enable users to leverage AI's advantages and capabilities in an appropriate manner.

Beyond the institutional and organisational level, findings from this research demonstrate the necessity of prompt actions at the policymaker level to balance innovation with educational integrity. Policymakers need to design and develop sector-wide guidelines that enable universities to harness Gen AI's augmentative capabilities while safeguarding against its attenuating effects on student learning. These guidelines should recognise the ecosystem-level implications of Gen AI, acknowledging that technology acts as a novel actor with assistive agency rather than merely a passive tool. Furthermore, as evidenced by this study, Gen AI has already entered this ecosystem. In such a situation, to maintain academic integrity while enabling the legitimate use of Gen AI, policymakers should mandate transparency and disclosure requirements for AI use in higher education contexts.

Operationalising these guidelines requires clear national standards for Gen AI integration into the higher education ecosystem. Such standards should address crucial dimensions that enable policymakers to balance AI-enabled innovation with academic integrity. First, transparency and disclosure requirements should mandate higher education service providers to clearly outline and publish AI usage policies with a focus on permitted and prohibited use across different contexts (i.e. teaching, research, assessment). Second, academic integrity frameworks should provide clarity on what constitutes appropriate augmentation versus inappropriate automation. Third, data protection and ethical usage should ensure that educational and research AI applications handle staff and students' data. Fourth, student protection measures should create safeguards ensuring that Gen AI integration does not disadvantage students from different socioeconomic backgrounds. Together, these dimensions provide actionable insights through which policymakers can operationalise this study's findings, ensuring Gen AI enhances rather than undermines the value propositions offered by higher education service providers.

### 4.6. Conclusion

The study's exploration of Gen AI in the higher education ecosystem reveals a complex and dynamic technological intervention that fundamentally reshapes traditional academic practices. While Gen AI demonstrates significant potential in augmenting knowledge creation and dissemination activities for academic staff, it simultaneously raises critical concerns about knowledge integrity, particularly in student learning contexts. The research introduces Gen AI not merely as a technological tool but as an emerging ecosystem actor with distinctive capabilities and limitations. By providing a novel perspective that views technology as an active participant rather than a passive instrument, this study challenges existing conceptualisations of technological integration in educational settings.

## References


Adeinat, I. M., & Abdulfatah, F. H. (2019) Organizational culture and knowledge management processes: case study in a public university. *VINE Journal of Information and Knowledge Management Systems*, 49(1), 35-53.

Adner, R. (2006) Match your innovation strategy to your innovation ecosystem. *Harvard Business Review*, 84(4), 98-107.

Adner, R. (2017) Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, 43(1), 39-58.

Altbach, P. G. (2011) The Past, Present, and Future of the Research University. *Economic and Political Weekly*, 46(16), 65-73.

Baldwin, C. Y., & Clark, K. B. (2000) *Design Rules, Volume 1: The Power of Modularity* (1st ed., Vol. 1). MIT Press.

Bano, S., & Taylor, J. (2015) Universities and the knowledge-based economy: perceptions from a developing country. *Higher Education Research & Development*, 34(2), 242-255.

Barros, A., Prasad, A., & Śliwa, M. (2023) Generative artificial intelligence and academia: Implication for research, teaching and service. *Management Learning*, 54(5), 597-604.

Braun, V., & Clarke, V. (2006) Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77-101.

Brown, O., Davison, R. M., Decker, S., Ellis, D. A., Faulconbridge, J., Gore, J., Greenwood, M., Islam, G., Lubinski, C., MacKenzie, N. G., Meyer, R., Muzio, D., Quattrone, P., Ravishankar, M. N., Zilber, T., Ren, S., Sarala, R. M., & Hibbert, P. (2024) Theory-Driven Perspectives on Generative Artificial Intelligence in Business and Management. *British Journal of Management*, 35(1), 3-23.

Brynjolfsson, E., & McAfee, A. (2017) The business of artificial intelligence. *Harvard Business Review*, 7(1), 1-2.

Budhathoki, T., Zirar, A., Njoya, E. T., & Timsina, A. (2024) ChatGPT adoption and anxiety: a cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). *Studies in Higher Education*, 49(5), 831-846.

Butler, N., & Spoelstra, S. (2025) Algorithmic management learning. *Management Learning*, 56(1), 132-139.

Eisenhardt, K. M., Santos, F. M., Pettigrew, I. A., Thomas, H., & Whittington, R. (2000) Knowledge based view. *Handbook of strategy and management.* London: Sage Publications.

Essien, A., Bukoye, O. T., O'Dea, X., & Kremantzis, M. (2024). The influence of AI text generators on critical thinking skills in UK business schools. *Studies in Higher Education*, 49(5), 865-882.

Gao, L. (Xuehui), López-Pérez, M. E., Melero-Polo, I., & Trifu, A. (2024) Ask ChatGPT first! Transforming learning experiences in the age of artificial intelligence. *Studies in Higher Education*, 49(12), 2772-2796.

Grant, R. M. (1996) Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109-122.

Grimes, M., Von Krogh, G., Feuerriegel, S., Rink, F., & Gruber, M. (2023) From scarcity to abundance: Scholars and scholarship in an age of generative artificial intelligence. *Academy of Management Journal*, 66(6), 1617-1624.

Henderson, J., Norris, C., & Hornsby, E. R. (2024) Refining Higher Education's Core Competence and Its Shaping Influence on the Future of Learning and Work. *Research Issues in Contemporary Education*, 9(2).

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

Krammer, S. M. S. (2023) Is there a glitch in the matrix? Artificial intelligence and management education. *Management Learning*. doi.org/10.1177/13505076231217667

Kulkarni, M., Mantere, S., Vaara, E., van den Broek, E., Pachidi, S., Glaser, V. L., Gehman, J., Petriglieri, G., Lindebaum, D., Cameron, L. D., Rahman, H. A., Islam, G., & Greenwood, M. (2024) The Future of Research in an Artificial Intelligence-Driven World. *Journal of Management Inquiry*, 33(3), 207-229.

Kung, T. H., Cheatham, M., Medenilla, A., Sillos, C., De Leon, L., Elepaño, C., Madriaga, M., Aggabao, R., Diaz-Candido, G., Maningo, J., & Tseng, V. (2023) Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models. *PLOS Digital Health*, 2(2).

Larson, B. Z., Moser, C., Caza, A., Muehlfeld, K., & Colombo, L. A. (2024) Critical thinking in the age of generative AI. *Academy of Management Learning & Education*, 23(3), 373-378.

Lune, H., & Berg, B. L. (2017) *Qualitative research methods for the social sciences*. Pearson.

Mollick, E. & Mollick, L. (2023) Using AI to implement effective teaching strategies in classrooms: Five strategies, including prompts. Working paper. doi:10.2139/ssrn.4391243

Nguyen, A., Hong, Y., Dang, B., & Huang, X. (2024) Human-AI collaboration patterns in AI-assisted academic writing. *Studies in Higher Education*, 49(5), 847-864.

Nickerson, J. A., & Zenger, T. R. (2004) A knowledge-based theory of the firm—The problem-solving perspective. *Organization Science*, 15(6), 617-632.

Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company : how Japanese companies create the dynamics of innovation. Oxford University Press.

O'Dea, X. (2024) Generative AI: is it a paradigm shift for higher education?. *Studies in Higher Education*, 49(5), 811-816.

Roumeliotis, K. I., & Tselikas, N. D. (2023) Chatgpt and open-ai models: A preliminary review. *Future Internet*, 15(6), 192.

Rowley, J. (2000) Is higher education ready for knowledge management?. *International Journal of Educational Management*, 14(7), 325-333.

Spender, J. C. (1996) Making knowledge the basis of a dynamic theory of the firm. *Strategic Management Journal*, 17(S2), 45-62.

Stokel-Walker, C. (2023) ChatGPT listed as author on research papers: Many scientists disapprove. *Nature*, 613, 620-621.

Susnjak, T., & McIntosh, T. R. (2024) Chatgpt: The end of online exam integrity?. *Education Sciences*, 14(6), 656.

Teece, D. J. (2018) Profiting from innovation in the digital economy: Standards, complementary assets, and business models in the wire-less world. *Research Policy*, 47 (8), 1367-1387.

Wang, X., Liu, Q., Pang, H., Tan, S. C., Lei, J., Wallace, M. P., & Li, L. (2023) What matters in AI-supported learning: A study of human-AI interactions in language learning using cluster analysis and epistemic network analysis. *Computers & Education*, 194, 104703.

Yang, Y., Luo, J., Yang, M., Yang, R., & Chen, J. (2024) From surface to deep learning approaches with Generative AI in higher education: an analytical framework of student agency. *Studies in Higher Education*, 49(5), 817-830.

Yin, R. K. (2009) *Case study research: Design and methods* (5th ed.). SAGE.

Zhao, L., Rahman, Md. H., Yeoh, W., Wang, S., & Ooi, K.-B. (2024). Examining factors influencing university students' adoption of generative artificial intelligence: a cross-country study. *Studies in Higher Education*, 1–23.

# Chapter 5: Discussion

This thesis advances knowledge regarding the organisational aspects of AI. As a technological phenomenon, AI has experienced tremendous progress from a technical point of view. However, despite the wide adoption of AI by different organisations and the potential opportunities and threats associated with this adoption, the organisational aspects of this cutting-edge technology have not been studied in enough depth. This thesis makes significant contributions towards organisational studies on AI through an SLR and two empirical research papers.

## 5.1. Implications for theory

The first paper in Chapter 2 focused on the following research question*: How can AI be managed within the Digital Transformation (DT) process of organisations?* In this regard, this paper systematically reviewed empirical studies in the literature on AI-based DT. Findings from this review informed the design of a conceptual model that demonstrates how AI can be managed within the DT process. The proposed model, by going beyond conventional technological enablers required for AI-based DT (i.e., data and structure), introduced other types of enablers (i.e., organisational and environmental enablers) essential for AI-based DT. Additionally, the model offered distinct strategies through which AI-based DT can be carried out. Automation, augmentation, and co-creation are three approaches offered by this model through which organisations can pursue their DT process enabled by AI. Among these strategies, automation focuses on automating routine tasks, while augmentation aims to enhance human capabilities in task performance. In contrast, co-creation emphasises the necessity for holistic transformation in both business models and the broader organisational ecosystem when implementing AI within DT processes. This model argued that these strategies are followed in an evolutionary approach by their adopters. This approach implies that an organisation implementing AI-based DT through the co-creation strategy is also capable of pursuing augmentation and automation strategies. Similarly, an organisation carrying out AI-based DT through the augmentation approach is simultaneously able to adopt the automation strategy. Furthermore, this model identified exclusive positive outcomes associated with each of these strategies, while also recognising generic negative outcomes linked to AI-based digital transformation, regardless of the selected strategy.

Regarding the positive outcomes associated with AI-based DT, most studies that identified these outcomes adopted particular types of theoretical lenses, such as the resource-based view of the firm (RBV), dynamic capabilities, and knowledge-based view of the firm (KBV). These theories have a specific focus on the crucial resources that can enable organisations to gain and sustain competitive advantages. From this perspective, AI can be viewed as a critical resource whose adoption by organisations can provide competitive advantages. Alongside these positive outcomes, a wide range of negative consequences are also associated with AI-based DT. Among the studies reviewed in the SLR paper, these negative outcomes were mostly reported by research papers conducted from the work-related perspective. The sectoral focus of these studies covers a wide range of industries, such as manufacturing, transportation, and wholesale. This finding demonstrates that regardless of the sector, work-related concerns and issues are among the most important challenges associated with AI-based DT.

Moreover, among the studies reviewed that introduced executive strategies for carrying out AI-based DT, those that introduced automation and augmentation utilised a wide range of theoretical perspectives. The diversity of these theoretical lenses reflects the functional approaches to these strategies (i.e. automation and augmentation). These strategies are typically adopted for specific and narrowly defined areas to either automate routine tasks (a hotel room booking system) or enhance humans' capabilities (assisting radiologists in image analysis). In line with this functional approach, the underlying theoretical perspectives of these strategies are contextual. In contrast, the co-creation strategy, as a comprehensive approach whose primary focus is on substantial changes in the business model and ecosystem, was predominantly found across studies that utilised unified theoretical perspectives, such as business model and ecosystem.

Findings from the SLR paper on augmentation strategy informed the empirical focus of this thesis. In this regard, the second research paper in Chapter 3 focused on addressing the following research question: *How can augmented intelligence be managed in the innovation practices of knowledge-based firms?* This study adopted qualitative research methodology and examined five start-ups from the knowledge-intensive sector. Viewing organisations from the KBV perspective, knowledge creation and utilisation are the two most crucial activities carried out by knowledge-intensive organisations (Sveiby, 2001; Schulz, 2001; Grant, 1996; Grant and Baden-Fuller, 1995). The centrality and significance of these processes have made them ideal contexts for the emergence of innovation practices enabled by cutting-edge technologies. This means that when cutting-edge technologies are integrated into knowledge-intensive organisations, knowledge creation and utilisation processes become prime targets for innovation. From this perspective, the selected cases were examined to find out how their knowledge creation and utilisation processes are altered and innovated by introducing AI. Empirical findings from these cases informed the design of a theoretical framework that introduces different innovation practices comprising augmented intelligence through the collaboration between AI and HI.

Rooted in the bounded rationality concept, KBV theory argues that knowledge-related processes depend on the diverse specialised knowledge carried out by individual specialists (Grant 1996; Grant, 2013). This argument has been built upon the assumption that humans with bounded rationality are the only types of organisational intelligent agents, and thus, specialisation is required to overcome limitations stemming from human cognitive constraints. In this context, the proposed division of tasks between AI and HI by conceptualising AI as a new type of knowledge specialist whose rationality is not limited in the way that humans are makes a profound contribution towards KBV theory.

First, in the realm of the KBV theory, the creation and utilisation of knowledge have traditionally been viewed as processes carried out exclusively by the agency of humans, who are considered the sole intelligent agents within organisations (Grant 1996). However, the second research paper in Chapter 3 argued that when knowledge creation and utilisation processes are altered by the incorporation of AI, HI is no longer the only intelligent agent carrying out these processes. This is because AI can transcend its role as a conventional tool serving HI and actively collaborate as a novel intelligent agent. This represents a significant contribution that the second research paper of this thesis makes to the KBV theory by introducing a non-human intelligent agent into processes that have traditionally depended solely on HI. Furthermore, this paper, by proposing a division of tasks between AI and HI across each of the identified innovation practices, clearly explains the distinct roles that AI and HI can play within knowledge creation and utilisation processes.

Second, findings from the research paper in Chapter 3 demonstrated that humans are no longer the only individual specialists. This assertion implies that AI can now act as new specialists whose functionality spans a wide range of different areas, from utilisation and creation of explicit knowledge to empowering HI in creation and utilisation of tacit knowledge. This means in the age of AI, rather than viewing specialisation as a response to bounded rationality, it should be reframed as a strategic design to leverage the advantages provided by AI and HI as the two types of organisational intelligence. This represents a fundamental shift in how specialisation is defined by reconceptualising it as a phenomenon born of bounded rationality to a concept born from augmented intelligence.

Third, having AI as a new type of specialist means that traditional coordination challenges stemming from integrating humans with specialised knowledge may no longer exist. AI's novel capabilities, such as functioning as a knowledge-integration platform and synthesising explicit knowledge from different sources, facilitating efficient knowledge transfer and integration by standardising knowledge formats, and enabling asynchronous knowledge coordination while maintaining organisational memory by operating as a persistent knowledge repository, can alleviate traditional coordination challenges recognised by KBV. However, the integration of AI-created explicit knowledge with human tacit knowledge may cause new coordination challenges tailored to AI-HI settings, which has not beet address by the KBV theory and its broader literature.

Fourth, the cooperation challenges recognised by traditional KBV can also be altered in the age of AI. Unlike human specialists, AI does not have personal goals that may conflict with organisational objectives. Moreover, AI can perform unbiased analysis, which reduces the chances of conflicts rooted in misinterpretations. For these reasons, having AI as a new type of specialist can resolve some of the cooperation challenges that happened when humans were the only specialised individuals. However, as AI systems need training, monitoring, and validation, new types of cooperation mechanisms may be needed that differ from traditional human-human cooperation.

Fifth, as mentioned earlier, from the KBV perspective, HI has traditionally been considered the only intelligent agent with a crucial role in the creation and utilisation of knowledge. However, this view has been complemented by taking into account the type of knowledge that is created and utilised. In this regard, there is a long-standing discourse in the KBV literature arguing that while some potential exists for allocating the creation and utilisation of explicit knowledge to non-human intelligence, these processes are exclusively carried out by humans when knowledge is in its tacit form. In such a context, the division of tasks proposed by this study constitute another important contribution to the KBV theory. According to this division of tasks between AI and HI across the innovated knowledge creation and utilisation processes, AI cannot only participate in the creation and utilisation of explicit knowledge as a sole agent, but it can also contribute to the creation and utilisation of tacit knowledge by empowering HI in working with this type of knowledge. This represents a novel and significant contribution to the KBV theory, as it recognises, for the first known time, the role of non-human intelligence (i.e. AI) within the creation and utilisation of tacit knowledge.

In Chapter 4, the third paper focused on addressing the following research question*: How can Gen AI affect the proposed value of a knowledge-based institution's ecosystem?* Drawing on the ecosystem-as-structure perspective and focusing on a higher education service provider, Lancaster University Management School (LUMS), as a representative case for knowledge-based institutions, this research paper examined how Gen AI affects both value propositions and crucial activities to create these value propositions within the higher education ecosystem. Using a qualitative research method, the study gathered novel empirical evidence by examining academicians' perspectives on Gen AI's role in knowledge creation and dissemination. This research paper made significant contributions towards the emerging literature on ecosystem perspective and Gen AI in the higher education ecosystem. The first theoretical contribution of this research paper is studying higher education service providers from an ecosystem perspective. To the best of my knowledge, this is the first study that adopts the ecosystem perspective to examine non-profit institutions like universities through the lens of theory and perspective that emerged with a particular focus on competition across for-profit organisations. Adopting such a novel perspective enabled the depiction of a rich picture of the value propositions offered by universities, the required activities performed by academic staff to create these value propositions, and the roles academic workforce play in these activities. Furthermore, by introducing an augmentation role for Gen AI, this study demonstrated that integration of Gen AI into the higher education ecosystem occurs through collaboration between academic staff and Gen AI rather than through the replacement of these human experts.

This paper also made a significant contribution to the ecosystem literature by viewing technology (i.e. Gen AI) as an active ecosystem player rather than a passive tool. The ecosystem perspective, as an emerging stream of knowledge in the strategic management field, is primarily focused on multilateral interactions between actors whose activities are interdependent. Among different proposed definitions for ecosystem perspective, ecosystem-as-structure was selected as the theoretical lens for this study. This particular definition of ecosystem focuses on the required activities performed by different actors for creating an ecosystem's value propositions. In the context of the chosen case study, LUMS, the actors typically include academic staff members, students, professional services staff members, businesses, policymakers, government, and other universities. In such a context, findings from this study revealed that Gen AI can affect the higher education ecosystem's proposed values by introducing itself as a new player with an assistive role in knowledge creation and knowledge dissemination activities. Viewing Gen AI as a novel actor positions it as a distinctive actor with its unique identity distinguished from the other ecosystem actors. Whilst viewing technology as a key ecosystem component is not novel, this study's significant contribution to ecosystem studies literature lies in reconceptualising Gen AI as a technology-enabled actor that actively participates in core activities and collaborates with other ecosystem players.

The ecosystem-as-structure perspective, by adopting an activity-centric approach to ecosystem, has a particular emphasis on the interdependent activities required to realise the value propositions offered by ecosystems. Drawing on this angle, the research paper in Chapter 4 demonstrated the reconfiguration in ecosystem's activities, conceptualised as a profound shift in modality of activities that underlie the value propositions of ecosystems. These empirical findings revealed how modality of knowledge creation and knowledge dissemination activities are reconfigured by introduction of Gen AI as an active actor into the higher education ecosystem. This impact is recognised as a positive activity-level reconfiguration, where Gen AI, by playing its assistive role, augments academic staff in their knowledge-related activities. However, findings revealed another dimension of activity-level ecosystem reconfiguration that is more problematic as students start to utilise Gen AI to bypass rather than augment essential learning activities. This approach to use Gen AI by students imposes destructive impacts on educational value proposition offered by higher education ecosystem. Empirical evidence from this dual nature of activity-level reconfiguration made a profound theoretical contribution to the ecosystem-as-structure perspective. According to this contribution, it can be said that while ecosystem reconfigurations enabled by Gen AI can be beneficial, they can be simultaneously detrimental within the same system, contingent upon actor positioning, activity type, and the nature of interaction between human and technology-enabled actors. This argument advances the ecosystem-as-structure and its broader literature by addressing novel and unique contexts in the age of Gen AI.

### 5.2. Implications for practice

Regarding AI-based DT, the first paper unfolds three practical implications. First, by presenting both positive and negative outcomes associated with AI-based DT, the proposed conceptual model enables organisations to develop a clearer and more realistic outlook regarding the benefits and risks of this transformation. This realistic approach allows organisations to leverage the advantages of AI-based DT while simultaneously preparing to mitigate its potential adverse impacts. Second, alongside technological enablers, the proposed conceptual model in this paper presents organisational and environmental enablers that influence AI-based DT. As a technological concept, AI is predominantly examined from a technical perspective, while its organisational and environmental aspects have been less addressed. In this context, the proposed model comprehensively introduces technological, organisational, and environmental enablers of AI-based DT. This holistic approach helps organisations manage their AI-based DT more effectively and with fewer challenges. The third practical implication of the SLR paper stems from the executive strategies it proposes for AI-based DT. According to these strategies, depending on their goals for AI-based DT, organisations can either: focus on the automation capabilities of AI to automate a set of tasks across narrowly defined areas; concentrate on the augmentation role of AI to enhance the human capabilities and expertise; or ultimately design new business models enabled by AI's distinctive features.

Innovations enabled by the emergence of cutting-edge technologies have long been one of the main resources that provide organisations with competitive advantages. Benefiting from these innovations requires immediate and informed actions from adopters. Across different types of organisations, taking such action is more crucial for start-ups due to their limited resources compared to established organisations and the higher competition they face. The importance of such informed and effective actions is more significant when the adopted cutting-edge technology is AI, and the adopters are knowledge-intensive start-ups. This is because AI is not only evolving at a frantic pace but also demonstrating human-comparable intelligence across specific types of tasks, which opens up significant opportunities for utilisation by knowledge-intensive start-ups. In this context, the second research paper in Chapter 3 offers a robust framework that can assist knowledge-intensive start-ups to utilise AI efficiently and with less trial and error. This framework, by demonstrating which knowledge processes should be allocated to AI versus HI based on problem novelty and solution transferability, provides actionable guidance for AI implementation. The proposed framework enables start-ups to strategically design AI-HI collaboration models that leverage AI's capabilities while preserving human expertise in tacit-knowledge domains. Moreover, the proposed four innovation pathways can enable start-ups to assess their AI readiness, optimise resource allocation between contextual versus transferable solutions, and build sustainable competitive advantage through systematic augmented intelligence practices. The practical implications of the research paper in Chapter 3 are not solely limited to start-ups. Indeed, they provide actionable insights for established organisations to utilise AI alongside their human expertise in an appropriate way. Established organisations can use these frameworks to redesign both their current workflows and how knowledge is used in their organisations, determine when they need to pursue solutions to common problems in a more efficient manner (Innovation Practice I and II) or breakthrough innovations through novel problem-solving (Innovation Practice III and IV), and implement proper coordination mechanisms between AI explicit-knowledge processing and human tacit-knowledge creation to achieve both efficiency gains and enhanced innovation capacities.

The third research paper in Chapter 4 offers practical recommendations, tailored to higher education institutional leaders and managers, policymakers and regulators, and technology providers. The implementation of these recommendations can enhance the value propositions offered by knowledge-based institutions in the age of Gen AI.

The first group of practical implications of the third research paper in Chapter 4 targets higher education institutional leaders and managers. In this regard, empirical findings revealed that this group of stakeholders needs to develop differentiated AI governance frameworks to recognise Gen AI's dual role as both augmenting and potentially attenuating technology. Such governance can be achieved only through establishing cross-functional AI governance committees comprising representatives from different groups of beneficiaries and contributors (i.e. technology providers, academic staff, students, legal experts, and faculty bodies) to oversee AI initiatives and ensure alignment with institutional values. This is a crucial effort to address the dual and paradoxical impacts of Gen AI on value propositions offered by higher education service providers. Moreover, to cope with the challenges of attenuated knowledge dissemination, this group of stakeholders needs to redesign assessment strategies in a way that students' critical thinking development is preserved while they use Gen AI.

Alongside the proposed revisions in assessment strategies, universities need to establish mandatory courses that train students to use Gen AI as an augmentation tool rather than an automation substitute. These programmes should enhance students' critical thinking in the age of Gen AI, making them familiar with potential biases and limitations embedded in AI systems, and clearly distinguish for them pedagogically sound augmentation approaches from academically problematic uses. Additionally, academic staff should participate in mandatory training programmes to understand the best practices for using Gen AI within research and teaching activities, while their higher-order intellectual skills are preserved and enhanced.

Technology firms shape the second group of audiences for the practical contributions that the research paper in Chapter 4 made. As findings from this research paper revealed, Gen AI's positive impacts on value propositions offered by the higher education ecosystem are significantly associated with its augmentation role. In this regard, technology firms that develop AI-based solutions for the higher education ecosystem should be advised to focus on this aspect of Gen AI rather than its automation capabilities. These firms are strongly advised to design educational AI solutions with built-in constraints that require human intellectual contributions. In practice, this means that AI-based solutions should be designed to provide suggestions, questions, and critiques rather than producing the final answer. To achieve these goals, it is recommended that technology service providers collaborate with prospective users and stakeholders (e.g. academic staff and students) in their design and delivery phases. This kind of collaboration is helpful for ensuring that AI-based solutions are co-designed in a way that supports learning goals rather than undermining them.

Policymakers and regulators are the last group of audiences for practical contributions made by the research paper in Chapter 4. In this regard, the empirical findings demonstrated the significant need for action from policymakers at the national level to balance innovation with educational integrity. For this aim, this group of stakeholders needs to design and develop sector-wide guidelines to support and encourage universities to focus on Gen AI's augmentative capabilities and safeguard against its attenuating impacts on students. Recognising the ecosystem-level implications of Gen AI, these guidelines should acknowledge that technology functions as a novel actor with assistive agency rather than merely a passive infrastructural tool. Operationalising these guidelines needs transparent standards set at the national level. Policymakers and regulators must design standards that ensure the addressing of social, economic, and legal dimensions required to balance AI-enabled innovation with academic integrity. The first group of these standards should mandate higher education institutions to clearly outline and publish AI policies that introduce the permitted and prohibited usage of Gen AI in this context. Second, robust academic frameworks should be designed and shared with higher education institutions to ensure enough clarity on what constitutes appropriate augmentation versus inappropriate automation. Such an effort should be complemented by comprehensive insights on data protection and ethical usage of Gen AI in the higher education context. Finally, these standards must mandate safeguards to ensure that Gen AI integration does not disadvantage students from different socioeconomic backgrounds.

### 5.3. Limitations and directions for future research.

Regarding the SLR paper, several limitations should be considered. First, although thorough and robust efforts have been made to avoid any bias within the systematic literature review process (i.e. searching and selecting included studies), it is impossible to guarantee that the final sample of the gathered publications is bias-free. This means that some relevant studies may have been inadvertently excluded. This potential omission could affect the completeness of the evidence base addressing the research question. Second, the final sample consists of studies conducted across multiple sectors, whilst the proposed conceptual model in this study offers generic insights that are not confined to any specific industry. This breadth, although valuable for generalisability, presents a limitation since the model is derived from contextual evidence from diverse sectoral settings that can affect its applicability to narrowly defined industrial sectors. The third limitation stems from the lack of consensus on AI’s definition. This limitation imposed challenges for utilising appropriate technical search keywords to find studies focused on AI as a DT enabler. In this regard, this study draws on the definition of AI as a technology that focuses on sophisticated algorithms’ learning to perform certain tasks as intelligent as humans by exploiting extensive quantities of data (Baird and Maruping, 2021; Haenlein and Kaplan, 2019; Jordan and Mitchell, 2015). Having such a view on AI's definition enables this study to consider particular technical phenomena (e.g. machine learning, deep learning, data analytics, and digital assistants) as the other representation of AI due to the same functionality they have in learning intelligent behaviour by exploiting a substantial volume of data, and thus, including them in the search criteria.

The SLR paper suggests several avenues for future research. First, the findings show that examining AI-based DT across particular sectors such as retailing, banking, and healthcare has been less extensively investigated. This gap suggests that these sectors are the potential areas where scholars should consider conducting studies focused on AI-based DT. Second, although the proposed model introduces a clear connection between the type of executive strategies for AI-based DT and resulting positive outcomes, such a linkage between different enablers (i.e. organisational, technological, and environmental enablers) and executive strategies was not found. In other words, although this study reveals what types of positive outcomes are associated with each of the proposed strategies for AI-based DT, it does not provide any insights on what kinds of enablers may be exclusively required for each of these strategies. This gap presents another avenue for future studies where researchers could examine potential connections between executive strategies and particular types of organisational, technological, and environmental enablers. Third, the conceptual model designed in this study can be used and examined by scholars across different sectors. This approach not only validates the credibility of the model through empirical testing but also provides an opportunity for the model to be updated and complemented through examination with empirical findings from diverse contexts.

Regarding the second paper (Chapter 3), the main limitation comes from its contextual focus. This paper draws on the KBV theory, particularly focused on organisations that treat knowledge as their main resource for value creation. Furthermore, the studied cases were selected among start-ups that represent different characteristics compared to established organisations. These contextual orientations can cause potential challenges to the generalisation of findings, which is one of the main limitations of qualitative research methods and multiple case study settings. This limitation simultaneously offers new avenues for future research. Organisation and management scholars with a particular focus on organisational aspects of AI have the opportunity to apply and examine the designed model in this study across other sectors and non-start-up organisations for further explorations. Empirical evidence from these new contexts can enhance the external validity of the designed models by updating and complementing these models.

The third research paper (Chapter 4) is also associated with limitations rooted in its adopted research method. This study by utilising the single case study method, primarily focuses on examining how Gen AI can affect the proposed values offered by the higher education ecosystem from the academic staff members' points of view. Despite the crucial role that these academic staff members play in creating the value propositions offered by the higher education ecosystem, this group of actors are not the only players that shape the higher education ecosystem. Indeed, drawing on the ecosystem-as-structure perspective, a range of other actors (e.g. students, professional services staff, government, business partners, and other universities) can be considered. Alongside academic staff members, these groups of actors also make a significant contribution towards the creation of value propositions offered by the higher education ecosystem. However, because of the inherited limitations in the single case study research method, this study was only focused on studying the impact of Gen AI on higher education ecosystem value propositions by obtaining empirical data from the academic staff members. Gathering empirical insights from only one of the groups of actors that comprise the higher education ecosystem can be considered the main limitation of this study. This limitation underlies the potential venues for future studies by other scholars. Future research can examine impact of Gen AI on the higher education ecosystem and its proposed values by focusing on the other actors that participate in the creation of value propositions offered by the higher education ecosystem. Furthermore, they can explore the potential interplays and dynamics between different groups of actors as the unit of analysis to examine impact of Gen AI on this sector.

## References


Baird, A., & Maruping, L. M. (2021) The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS Quarterly*, 45(1), 315-341.

Grant, R. M. (1996) Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109-122.

Grant, R. M., & Baden-Fuller, C. (1995) A knowledge-based theory of inter-firm collaboration. *Academy of Management Proceedings*, 1995(1), 17-21.

Grant, R. M. (2013) Reflections on knowledge-based approaches to the organization of production. *Journal of Management & Governance*, 17(3), 541-558.

Haenlein, M., & Kaplan, A. (2019) A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14.

Jordan, M. I., & Mitchell, T. M. (2015) Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255-260.

Schulz, M. (2001) The uncertain relevance of newness: Organizational learning and knowledge flows. *Academy of Management Journal*, 44(4), 661-681.

Sveiby, K. E. (2001) A knowledge-based theory of the firm to guide in strategy formulation. *Journal of Intellectual Capital*, 2(4), 344-358.

# Chapter 6: Conclusion

Technological innovations and the emergence of cutting-edge technologies, either by enhancing organisations' current offerings or enabling them to propose novel ones, have enabled organisations to transform and gain competitive advantages (Naimi-Sadigh et al., 2022; Vial, 2019; Hess et al., 2016; Demirkan et al., 2016; Zott and Amit, 2010; Teece, 1986). In this context, Artificial Intelligence (AI), as a cutting-edge technology capable of exhibiting human-like intelligence and producing human-like outputs, is considered one of the most important technological innovations that organisations can embrace (Hinds and von Krogh, 2024; Berg et al., 2023; Haenlein and Kaplan, 2019; Faraj et al., 2018; Brynjolfsson and McAfee, 2017). This thesis advances our understanding of AI and its transformative role in organisational contexts by moving beyond examining AI as merely another technological innovation to viewing it as a distinct form of intelligence associated with unique capabilities for organisational transformation. In other words, the main theoretical contribution of this thesis is the reconceptualisation of AI from a passive technological tool to an active organisational actor. This perspective shift is evident across three interconnected research papers in Chapters two, three and four, which all make significant contributions towards AI's role in contemporary organisations.

This thesis reveals that in the Digital Transformation (DT) context, AI emerges not simply as a kind of technology that should be implemented but as a dynamic enabler associated with technological, organisational, and environmental dimensions. Rather than exclusive focus on technological aspects of AI, this thesis demonstrates that a combination of technological, organisational, and environmental factors play a crucial role for AI-enabled DT. Moreover, this thesis advances the current literature on AI-based DT by introducing essential strategies that can be adopted by organisations for AI-based DT, followed by a wide range of positive and negative outcomes associated with AI-based DT.

This thesis makes a significant theoretical contribution by extending the Knowledge-Based View (KBV) of the firm to incorporate AI as a non-human intelligence contributor to knowledge processes. This thesis reveals that in the context of knowledge-intensive start-ups and from the KBV perspective, AI, by transitioning from a supporting technology to an intelligence capable of collaborating with human expertise in the form of augmented intelligence, plays the crucial role in knowledge creation and utilisation activities. Traditional KBV perspective has primarily focused on Human Intelligence (HI) as the only source of intelligence involved in knowledge creation and knowledge utilisation activities, and has viewed technology as a mere supportive infrastructure. In such a context, this thesis, by demonstrating how AI and HI can collaborate in the form of augmented intelligence, advances KBV theory to accommodate emerging AI capabilities.

Adopting an ecosystem-as-structure perspective, this thesis advances theoretical understanding of AI by viewing AI as an emergent actor within organisational ecosystems rather than a peripheral technology component. This perspective provides valuable insights into how AI, in general, and Generative AI (Gen AI), in particular, can influence value propositions and required activities to create these propositions in knowledge-intensive settings like higher education. In this context, by studying Lancaster University Management School (LUMS) through the ecosystem-as-structure lens, this thesis demonstrates how Gen AI can affect the value propositions traditionally centred on human expertise. This ecosystem-level analysis represents a theoretical contribution that extends firm-level or process-level studies of Gen AI implementation to consider broader patterns of value creation and actor relationships in AI-enhanced environments.

In conclusion, this thesis contributes to a more holistic understanding of AI's organisational impact by integrating insights across digital transformation processes, knowledge creation and knowledge utilisation activities, and ecosystem dynamics. By reconceptualising AI as a form of intelligence that collaborates with humans rather than merely as a technological tool, this research provides novel theoretical perspectives and practical guidance for organisations navigating the AI revolution. The following table (Table 6) demonstrates how three research papers conducted in this PhD project are connected.

Table 6. Summary of research papers

| Title of paper (chapter number) | Research aims | Findings |
|---|---|---|
| Managing artificial intelligence within the digital transformation process of organisations: A systematic review of the literature (Chapter 2) | This research aimed to understand how AI can be managed within the Digital Transformation (DT) process of organisations, by reviewing the corresponding literature systematically. | Alongside insights about the enablers of AI-based DT and outcomes associated with this journey, findings from this research revealed that organisations have three specific strategies for managing AI within their DT process: automation, which focuses on automating processes and operations; augmentation, which particularly focuses on collaboration between humans and AI; and co-creation, which underlies the required consideration of organisations' ecosystems and business models |

| | | |
|---|---|---|
| Managing augmented intelligence in innovation practices: Evidence from knowledge-intensive start-ups (Chapter 3) | Following the findings from the literature review, Chapter 3 of this research focused on examining augmented intelligence by gathering empirical evidence from knowledge-intensive start-ups, where Human Intelligence (HI) traditionally played a critical role and where, through the introduction of AI and an augmented intelligence strategy, novel collaboration patterns between AI and HI become possible. | Findings from this research demonstrated a division of tasks between AI and HI and illustrated how augmented intelligence (i.e., collaboration between HI and AI) can be managed across innovation practices by assigning distinct roles to HI and AI. Drawing on the Knowledge-Based View (KBV) of the firm, Chapter 3 of this research revealed that, contrary to the long-standing discourse on the solo role of HI in the creation and utilisation of tacit knowledge, AI contributes to tacit knowledge creation and utilisation by empowering HI in these processes, meaning that HI is no longer the only player in these processes. |
| Generative artificial intelligence in higher education: the ecosystem perspective (Chapter 4) | Following findings from the Systematic Literature Review (SLR) paper in Chapter 2 about the centrality of the ecosystem perspective when organisations follow the co-creation strategy for incorporating AI, Chapter 4 of this research, drawing on ecosystem-as-structure theory, studied how Gen AI can affect the value propositions of the higher education ecosystem. | Findings from this research paper (Chapter 4) revealed that Gen AI functions as an innovative ecosystem participant, enhancing specific functions whilst concurrently creating difficulties, especially regarding student education. This research advances the growing scholarly discourse on ecosystems, Gen AI applications in higher education, and educational innovation by exploring the multifaceted interactions between Gen AI and the players of the higher education ecosystem. |

## References


Berg, J. M., Raj, M., & Seamans, R. (2023) Capturing value from artificial intelligence. *Academy of Management Discoveries*, 9(4), 424-428.

Brynjolfsson, E., & McAfee, A. (2017) The business of artificial intelligence. *Harvard Business Review*, 7(1), 1-2.

Demirkan, H., Spohrer, J. C., & Welser, J. J. (2016) Digital innovation and strategic transformation. *IT Professional*, 18(6), 14-18.

Faraj, S., Pachidi, S., & Sayegh, K. (2018) Working and organizing in the age of the learning algorithm. *Information and Organization*, 28(1), 62-70.

Haenlein, M., & Kaplan, A. (2019) A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016) Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, 15(2), 123-139.

Hinds, P., & von Krogh, G. (2024) Generative AI, Emerging Technology, and Organizing: Towards a theory of progressive encapsulation. *Organization Theory*, 5(4), 1-14.

Naimi-Sadigh, A., Asgari, T., & Rabiei, M. (2022). Digital transformation in the value chain disruption of banking services. *Journal of the Knowledge Economy*, 13(2), 1212-1242.

Teece, D. J. (1986) Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6), 285-305.

Vial, G. (2019) Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, 28(2), 1-27.

Zott, C., & Amit, R. (2010) Business model design: An activity system perspective. *Long Range Planning*, 43(2-3), 216-226.

## Appendix A: Consent form

# CONSENT FORM

**Project Title: Strategies for managing artificial intelligence in innovation practices.**
Name of Researcher: Shayan Rashidi
Email: s.rashidi@lancaster.ac.uk
**Please tick each box**

| | | |
|---|---|---|
| 1. | I confirm that I have read and understand the information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily | ☐ |
| 2. | I understand that my participation is voluntary and that I am free to withdraw at any time during my participation in this study and within six weeks after I took part in the study, without giving any reason. If I withdraw within six weeks of taking part in the study my data will be removed. | ☐ |
| 3. | I understand that any information given by me may be used in future reports, academic articles, publications or presentations by the researcher/s, but my personal information will not be included and all reasonable steps will be taken to protect the anonymity of the participants involved in this project. | ☐ |
| 4. | I understand that my name/my organisation's name will not appear in any reports, articles or presentation without my consent. | ☐ |
| 5. | I understand that any interviews will be audio-recorded and transcribed and that data will be protected on encrypted devices and kept secure. | ☐ |
| 6. | I understand that data will be kept according to University guidelines for a minimum of 10 years after the end of the study. | ☐ |
| 7. | I agree to take part in the above study. | ☐ |

__________________________ ________________ _________________
Name of Participant Date Signature

**I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.**

**Signature of Researcher /person taking the consent**__________________________ **Date** ___________
Day/month/year

**One copy of this form will be given to the participant and the original kept in the files of the researcher at Lancaster University**

**Appendix B: Participant Information Sheet 1**

**Participant information sheet**

**Strategies for managing artificial intelligence in innovation practices**

| |
|---|
| For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/dataprotection |

I am a Post Graduate Researcher (PGR) at Lancaster University, and I would like to invite you to take part in a research study about: Strategies for managing artificial intelligence in innovation practices.

Please take time to read the following information carefully before you decide whether or not you wish to take part.

**What is the study about?**

This study aims to investigate how augmented intelligence (the integration of Artificial Intelligence (AI) and Human Intelligence (HI) can be managed in innovation practices of the private healthcare firms.

**Why have I been invited?**

You have been invited because of significant contribution that you can make towards understanding of how augmented intelligence (the integration of Artificial Intelligence (AI) and Human Intelligence (HI)) has been managed in the innovation practices of your firm. Your participation in this study will be sincerely appreciated.

**What will I be asked to do if I take part?**

If you decided to take part, this would involve the following:

The interview is expected to last for around 60-90minutes. During the interview, you, as an interviewee will be asked about the augmented intelligence in the innovation practices of your firm.

**What are the possible benefits from taking part?**

If you take part in this study, your insights will contribute to our understanding of how augmented intelligence can be utilised within the innovation practices of firms in which human intelligence plays the critical role and thus be more innovative.

**Do I have to take part?**

No. It's completely up to you to decide whether or not you take part. Your participation is voluntary. If you decide not to take part in this study, this will not affect your position in the company and your relations with your employer.

**What if I change my mind?**

If you change your mind, you are free to withdraw at any time during your participation in interview or before data analysis has been completed. If you want to withdraw, please let me know, and I will extract any ideas or information (=data) you contributed to the study and destroy them. However, it is difficult and often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data. Therefore, you can only withdraw up to 6 weeks after taking part in the interview.

**What are the possible disadvantages and risks of taking part?**

It is unlikely that there will be any major disadvantages to taking part. You only will be asked to take part in an interview for around 60-90 minutes.

**Will my data be identifiable?**

After the interview, only I, the researcher conducting this study will have access to the ideas you share with me, and my supervisors Professor Lola Dada, and Dr Richard Williams. All personal information about you (e.g., your name and other information about you that can identify you) will be kept confidential and will not be shared with others. Any personal information from the written record of your contribution will be removed. Furthermore, the anonymity of the case study firm will be considered, and its name will not be used in future reports, academic articles, publications or presentations by the researcher/s. Your participation in this study will be sincerely appreciated.

**How will we use the information you have shared with us and what will happen to the results of the research study?**

Your shared information will be used only in the following ways:

They will be utilised for research purposes only. This will include the PhD Thesis and journal articles in the management field. The results of this study may also be presented at academic conferences in this field in accordance with supervisors' guidance.

When writing up the findings from this study, I would like to reproduce some of the views and ideas you shared with me. I will only use anonymised quotes (e.g. from my interview with you), so that although I will use your exact words, all reasonable steps will be taken to protect the anonymity of you and your firm in our publications.

| **How my data will be stored** |
| --- |
| Your data, including anonymised transcripts of interviews will be stored in encrypted files on Lancaster University OneDrive until the PhD submission. After this time, the anonymised transcripts will be uploaded as a dataset to Lancaster University Research Data Repository (PURE) and will be kept according to the Lancaster University guidelines for a 10-year period. |

**What if I have a question or concern?**

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact myself through the following email address:

s.rashidi@lancaster.ac.uk. You also can contact my supervisors. The supervisors' details are as follows:

Professor Lola Dada, Department of Entrepreneurship and Strategy, Management School, Lancaster University

Email Address: l.dada@lancaster.ac.uk

Address: WP C065, C-Floor, Management School, Lancaster University, Lancaster, LA1 4YX, United Kingdom

Dr Richard Williams, Department of Management Science, Management School, Lancaster University

Email Address: r.williams4@lancaster.ac.uk

Address: B052a, B-Floor, Management School, Lancaster University, Lancaster, LA1 4YX, United Kingdom

If you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact: Dr Marian Iszatt-White, Department of Entrepreneurship and Strategy, Management School, Lancaster University

Email Address: m.iszattwhite@lancaster.ac.uk

Address: WP C091, C-Floor, Management School, Lancaster University, Lancaster, LA1 4YX, United Kingdom

This study has been reviewed and approved by the Faculty of Arts and Social Sciences and Lancaster Management School's Research Ethics Committee.

**Thank you for considering your participation in this project.**

**Appendix C: Participant Information Sheet 2**

**Participant information sheet**

**Artificial Intelligence (AI) and Innovation: Strategies for the application of AI in Innovation Practices**

| |
|---|
| For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/dataprotection |

I am a Post Graduate Researcher (PGR) at Lancaster University, and I would like to invite you to take part in a research study about: The application of AI in innovation practices.

Please take time to read the following information carefully before you decide whether or not you wish to take part.

**What is the study about?**

Drawing upon the ecosystem perspective, this study aims to investigate how AI can affect the proposed value of the knowledge-based firm's ecosystem. In this regard, Lancaster University Management School has been chosen as the representative case to be studied.

**Why have I been invited?**

You have been invited because of significant contribution that you can make towards understanding of how AI, and particularly Generative AI, can affect the value that Lancaster University Management School proposes to the Higher Education ecosystem as a knowledge-based organisation. Your participation in this study will be sincerely appreciated.

**What will I be asked to do if I take part?**

If you decided to take part, this would involve the following:

You are supposed to be interviewed for around 45 minutes. During the interview, you, as an interviewee will be asked how and under what circumstances AI in general, and Generative AI in particular, can affect the proposed value by Lancaster University Management School to its ecosystem, through studying the potential impact on the activities embedded in this ecosystem, players who carry out these activities, the positions that these players have against each other in this ecosystem, and the linkages between these players.

**What are the possible benefits from taking part?**

If you take part in this study, your insights will contribute to our understanding of how and under what circumstances AI, as a new type of intelligence, can be utilised in the area that have been traditionally dominated by Human Intelligence and what are the potential consequences of this utilisation from the ecosystem perspective.

**Do I have to take part?**

No. It's completely up to you to decide whether or not you take part. Your participation is voluntary. If you decide not to take part in this study, this will not affect your position in the company and your relations with your employer.

**What if I change my mind?**

If you change your mind, you are free to withdraw at any time during your participation in interview or before data analysis has been completed. If you want to withdraw, please let me know, and I will extract any ideas or information (=data) you contributed to the study and destroy them. However, it is difficult and often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data. Therefore, you can only withdraw up to 6 weeks after taking part in the interview.

**What are the possible disadvantages and risks of taking part?**

It is unlikely that there will be any major disadvantages to taking part. You only will be asked to take part in an interview for around 45 minutes.

**Will my data be identifiable?**

After the interview, only I, the researcher conducting this study will have access to the ideas you share with me, and my supervisors Professor Lola Dada, and Dr Richard Williams. All personal information about you (e.g., your name and other information about you that can identify you) will be kept confidential and will not be shared with others. Furthermore, any personal information from the written record of your contribution will be removed. All reasonable steps will be taken to protect the anonymity of the participants and firms that participate in our interviews. Your participation in this study will be sincerely appreciated.

**How will we use the information you have shared with us and what will happen to the results of the research study?**

Your shared information will be used only in the following ways:

They will be utilised for research purposes only. This will include the PhD Thesis and journal articles in the management field. The results of this study may also be presented at academic conferences in this field in accordance with supervisors' guidance.

When writing up the findings from this study, I would like to reproduce some of the views and ideas you shared with me. I will only use anonymised quotes (e.g. from my interview with you), so that although I will use your exact words, all reasonable steps will be taken to protect your anonymity in our publications.

| **How my data will be stored** |
|---|
| Your data, including anonymised transcripts of interviews will be stored in encrypted files on Lancaster University OneDrive until my PhD submission. After finishing my PhD, the anonymised transcripts will be uploaded as a dataset to Lancaster University Research Data Repository (PURE) and will be kept according to the Lancaster University guidelines for a 10-year period. |

**What if I have a question or concern?**

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact myself through the following email address: s.rashidi@lancaster.ac.uk. You also can contact my supervisors. The supervisors' details are as follows:

Professor Lola Dada, Department of Entrepreneurship and Strategy, Management School, Lancaster University

Email Address: l.dada@lancaster.ac.uk

Address: WP C065, C-Floor, Management School, Lancaster University, Lancaster, LA1 4YX, United Kingdom

Dr Richard Williams, Department of Management Science, Management School, Lancaster University

Email Address: r.williams4@lancaster.ac.uk

Address: D10, D-Floor, Charles Carter Building, Lancaster University, Lancaster, LA1 4YX, United Kingdom.

If you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact: Dr Marian Iszatt-White, Department of Entrepreneurship and Strategy, Management School, Lancaster University

Email Address: m.iszattwhite@lancaster.ac.uk

Phone Number:

Address: WP C091, C-Floor, Management School, Lancaster University, Lancaster, LA1 4YX, United Kingdom

This study has been reviewed and approved by the Faculty of Arts and Social Sciences and Lancaster Management School's Research Ethics Committee.

**Thank you for considering your participation in this project.**