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

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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 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 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.

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

Word Number: 6978

Introduction

Due to recent advancements in digital technologies such as Artificial Intelligence (AI), Digital Transformation (DT) has generated increased attention amongst academics and practitioners (Yang, 2022). DT has emerged as a concept that focuses on the incorporation of these digital technologies by organisations to alter 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 (Rego 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 the sheer volume of data. (Baird and Maruping, 2021; Haenlein and Kaplan, 2019; Jordan and Mitchel, 2015; Nilsson, 1971). From this point of view, a range of concepts, such as big data analytics capabilities, machine learning and deep learning algorithms, and applications such as digital assistants and robots, can be considered forms of AI technology that enable 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.

On the one hand, a considerable volume of data is generated daily; on the other hand, recent progress in computing power has made exploiting these data straightforward (Grønsund and Aanestad, 2020). For these reasons and due to the low dependency of AI algorithms' functionality on programming efforts compare to traditional information systems, AI seems to have much more transformative power than other emerging technologies (Brynjolfsson and McAfee, 2017).

However, despite the promises and opportunities associated with AI and its application, it cannot give any advantage to the organisation unless organisations 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 synthesis 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.

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).

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 was comprised of 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 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	“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	Search mode (Boolean operators of OR/AND); search fields (title, abstract or author-specified keywords); article type (research	Search mode (Boolean operators of OR/AND); search fields (article title, abstract, keywords); document type (article); subject area	Search mode (Boolean operators of OR/AND); search fields (title and abstract); document type (article); subject area (business and	Search mode (Boolean operators of OR/AND); search fields (title and abstract); document type (article); source type (scholarly

networks”, “computer vision”, “image recognition”, “speech recognition”, “digital assistants”, “virtual assistants”, “intelligence assistants”, “intelligence agents”, “intelligence systems”, “data analytics”, “big data analytics”, and “predictive analytics”		neural networks” OR “computer vision” OR “image recognition” OR “speech recognition” OR “digital assistants” OR “virtual assistants” OR “intelligence assistants” OR “intelligence agents” OR “intelligence systems” OR “data analytics” OR “big data analytics” OR “predictive analytics”) AND (“digital transformation” OR “digital disruption” OR “digital change”).	articles); subject areas (business, management and accounting); coverage period (up to February 2023), language (English)	(business, management and accounting); source type (journal); coverage period (up to February 2023), language (English)	management); coverage period (up to February 2023), language (English)	journals); coverage period (up to February 2023), language (English)
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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). On the one hand, DT is a business and managerial phenomenon that deals with digital technologies and their related consequences for organisations, regardless of the industrial context; on the other hand, this research was designed to find how and under what circumstances AI can be managed within DT process. For these reasons, the major focus of this study was on business and management field as it could help to find the best possible evidence from the literature. Finally, the search includes 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.

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, 2004). 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 unit of analysis, the number of times a given unit of analysis appeared in the sample was counted. Finally, to enable design of a conceptual model, inspired by the study conducted by Dada (2021), a visual map was utilised to show the relationships between the findings from the review in Figure 1 (Whetten, 1989).

Results

The whole 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, multiple sectors category 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-Khaatib (2023)	Positive outcomes (i.e. innovation)	Quantitative/ survey	Resource based view (RBV)	Big Data Analytics	Manufacturing	Jordan

				Capability (BDAC)		
Athota <i>et al.</i> (2023)	Positive outcomes (i.e. less uncertainty)	Qualitative/ interview	Attribution theory	Artificial Intelligence (AI)	Finance and Accounting	Australia
Christou <i>et al.</i> (2023)	Executive strategies (i.e. automation, augmentation)	Qualitative/ interview	Customer experience	Intelligent Automation (IA)	Tourism	Cyprus
Lozada <i>et al.</i> (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 <i>et al.</i> (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 (2022)	Positive outcomes (i.e. innovation)	Quantitative/ survey	Dynamic capabilities theory	Big Data Analytics (BDA)	Multiple (i.e. manufacturing and logistics)	Pakistan
Atuahene <i>et al.</i> (2022)	(1) Technological enablers (i.e. data, infrastructure) (2) Organisational enablers data-driven culture, citizen data scientist) (3) Environmental enablers (i.e. market pressure, competitor pressure, and governmental pressure)	Qualitative/ interview	Dynamic capabilities theory, Resource-based view (RBV) theory	Big data	Multiple (i.e. construction, consulting)	Australia
	Positive outcomes (i.e.					India

Bag <i>et al.</i> (2022)	customer engagement improvements)	Quantitative/survey	Consumer engagement theory	Artificial Intelligence (AI)	Multiple (i.e. government and private sector)	
Lin <i>et al.</i> (2022)	(1) Technological enablers (i.e. data) (2) Organisational enablers (i.e. citizen data scientist)	Quantitative/survey	Unknown	Deep learning	Healthcare	China
Papanagnou <i>et al.</i> (2022)	(1) Positive outcomes (i.e. less uncertainty) (2) Technological enablers (i.e. infrastructure)	Qualitative/interview	Dynamic capabilities theory	Big Data (BD) capabilities, Predictive analytics	Retailing	UK
Malik <i>et al.</i> (2022)	(1) Positive outcomes (i.e. work performance improvements) (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 <i>et al.</i> (2022)	(1) Technological enablers (i.e. data, infrastructure) (2) Organisational enablers (i.e. AI education for employees, citizen data scientist) (3) Executive strategies (i.e. augmentation)	Qualitative/interview	Technological reluctance theory	Big Data Analytics (BDA)	Finance and Accounting	New Zealand
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)	Colombia

Arias-Pérez and Vélez-Jaramillo (2022)	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 <i>et al.</i> (2022)	(1) Technological enablers (i.e. data) (2) Organisational enablers (i.e. AI education for employees)	Quantitative/survey	Technology acceptance model	Big Data Analytics (BDA)	Telecommunication	Greece
Lufi <i>et al.</i> (2022)	(1) Technological enablers (i.e. infrastructure) (2) Organisational enablers (i.e. leadership, AI education for employees, and organisational readiness) (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 <i>et al.</i> (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 education for employees)	Quantitative/survey	Diffusion of innovation theory, Technology Acceptance Model (TAM)	Artificial Intelligence (AI)	Government and public administration	US
Chatterjee <i>et al.</i> (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 (2022)	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,	Colombia

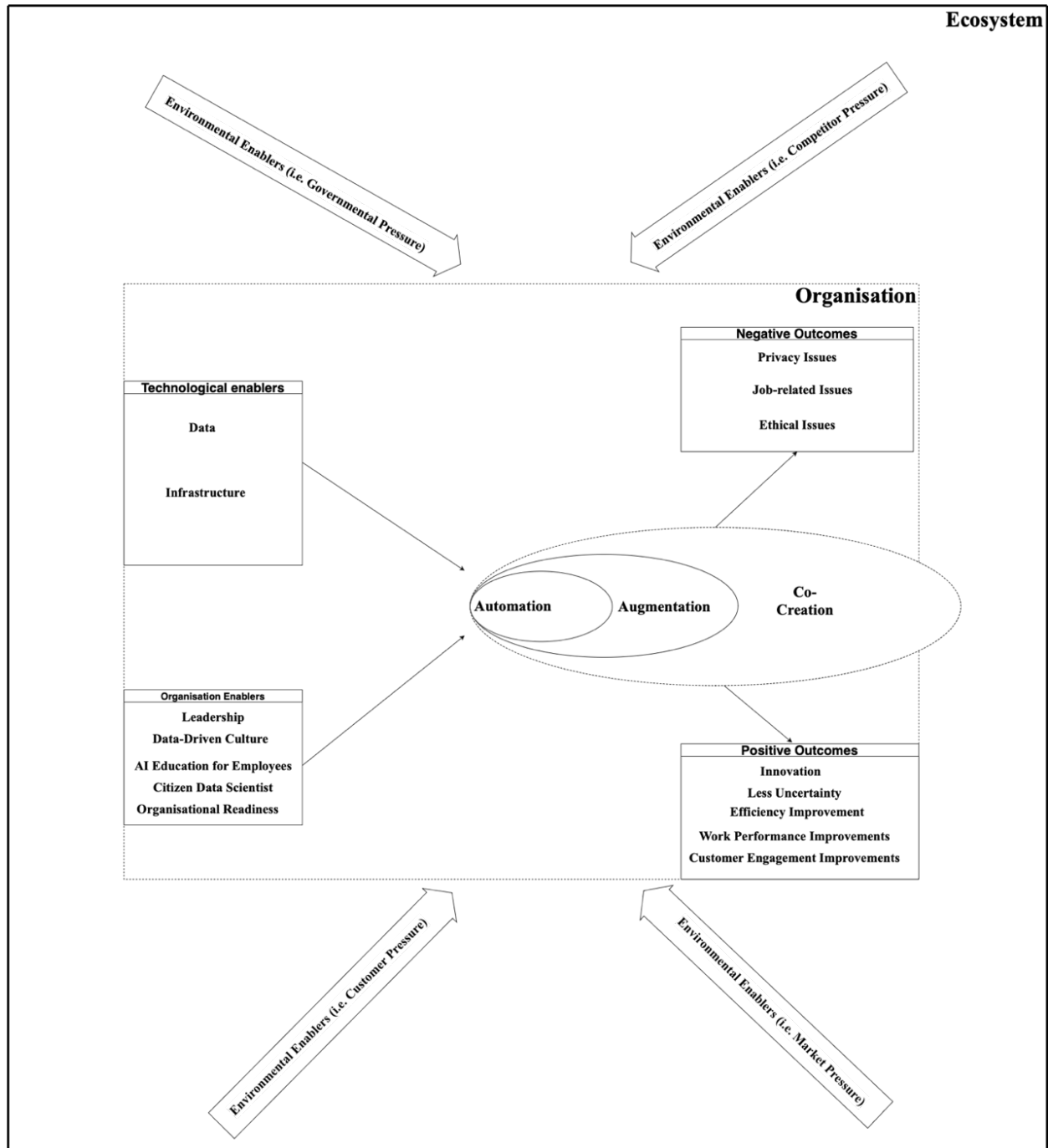
					telecommunication, wholesale and retail trade, education, architectural and engineering, and other knowledge-intensive, and low knowledge-intensive services	
De Andrade and Tumelero (2022)	(1) Positive outcomes (i.e. efficiency improvements)	Qualitative/ case study	Evolutionary theory of innovation	Chatbots	Banking	Brazil
Bodendorf <i>et al.</i> (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 <i>et al.</i> (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 <i>et al.</i> (2021)	(1) Positive outcomes (i.e. less uncertainty, work performance improvements) (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) (2) Organisational enablers (i.e. leadership, data-driven culture, and AI education for employees) (3) Environmental enablers (i.e. governmental pressure, market pressure, and competitors' pressure)	Qualitative/ Multiple case study	Technology adoption theory (Technology-Organisation Environment [TOE] framework)	Artificial Intelligence (AI)	Manufacturing	China

Frick <i>et al.</i> (2021)	Organisational enablers (i.e. leadership)	Qualitative and quantitative Interviews, survey	Empowering leadership perspective	Artificial Intelligence (AI)	Multiple (i.e. financial services, tattoo and body, and capital projects and infrastructure)	Unknown
Burstrom <i>et al.</i> (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 <i>et al.</i> (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 <i>et al.</i> (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 <i>et al.</i> (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 enablers (i.e. infrastructure) (2) Organisational enablers (i.e. leadership)	Qualitative/ interviews	Technology adoption perspective	Robotic Process Automation (RPA), Artificial Intelligence (AI)/ Machine Learning	Multiple (i.e. manufacturing and service firms)	Unknown

A conceptual model for AI-based DT

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 the relationship between them are depicted (Figure 1) and discussed in the following section.

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



Evidence from the review indicates two groups of potential outcomes associated with using AI for the DT of organisations. The first category belongs to positive outcomes, while the second category consists of the negative consequences of this process.

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, 2022; Papanagnou et al., 2022; Malik et al., 2022; Arias-Pérez and Cepeda-Cardona, 2022; De Andrade and Tumeler, 2022; Bag et al., 2022; Ballestar et al., 2021).

Four studies (Al-Khaatib, 2023; Lozada et al., 2023; Gao and Sarwar, 2022; 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-Khaatib, 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, 2022; Arias-Pérez and Cepeda-Cardona, 2022). These findings altogether suggest that DT based on AI's competencies enables organisations to be more innovative.

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. 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., 2022; 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 competitive 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.

On the one hand, inputs of AI algorithms are data that could be vulnerable to security and privacy issues; on the other hand, the process through which these input data 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.

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). 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.

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 et al. (2022) 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; Mourtzidis 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 et al. (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 et al. (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. On the other hand, 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 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.

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 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. The frequency of work-related perspectives employed by studies that reported negative outcomes and their diverse sectoral context indicate that irrespective of the industry for AI-based DT, job-related issues are among the most important concerns that require significant attention. Only one study conducted in the public administration sector focused on the ethical concerns associated with AI. The scarcity of

studies in this area shows that the economic consequences of AI have attracted more attention than ethical considerations.

This review further reveals a range of potential strategies for AI-based DT. Studies that reported automation and augmentation approaches as the potential 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. As discussed earlier, 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. In alignment 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 that affect the proposed strategies for the incorporation of AI into the DT process. 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. This issue indicates the importance of AI and the factors that can affect it to enable organisations to alter their value creation pathways and consequently gain competitive advantages. Considering these enabler factors is necessary for organisations to enjoy the associated merits of AI-based DT and lessen their severe effects.

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, as 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. Thus organisations can manage their AI-based DT process more efficiently.

Organisational enablers identified in this study allow organisations go beyond technological aspects by considering organisational and managerial issues that, although having a critical role in AI-based DT, have attracted less attention. 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 has several limitations that should be mentioned. First, despite the considerable effort that has been made to avoid any bias within the systematic literature review (searching and selecting), it is not possible to state that the final sample is bias-free. Second, as indicated in the result section, articles in the final sample came from diverse sectors. However, the proposed conceptual model and its associated factors are generic. Drawing generalised findings on contextualized evidence is another 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 the sheer volume of data (Nilsson, 1971; Jordan and Mitchel, 2015; Haenlein and Kaplan, 2019; Baird and Maruping, 2021), 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.

For future research, several suggestions can be made. 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.

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 the organisation 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*, In Press.
- 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. (2022) 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. (2022) 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) Artificial intelligence, for real. *Harvard Business Review*, 1, 1-31.
- 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*, 1-47.
- 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. (2022) How do firms create business value and dynamic capabilities by leveraging big data analytics management capability? *Information Technology and Management*, In Press.
- 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. (2004) *Content analysis: An introduction to its methodology*. Sage Publications.
- 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, 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*, In Press.
- 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*, In Press.
- 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.

- Nilsson, N. J. (1971) *Problem-solving methods in artificial intelligence*. New York: McGraw-Hill.
- 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.
- Plattfaute, 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*, 12(4), 1-28.
- 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.
- 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.
- Whetten, D. A. (1989). What constitutes a theoretical contribution? *Academy of management review*, 14(4), 490-495.
- Wixom, B. H., & Todd, P. A. (2005) A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, 16(1), 85-102.
- Yang, D. (2022) Evaluation of Enterprise Financial Risk Level under Digital Transformation with Artificial Neural Network. *Security and Communication Networks*, In Press.