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The relationship between digital technologies and innovation: A review, critique, and research agenda

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ABSTRACT

Digital technologies (DTs) have resulted in innovations that have fueled global knowledge-based economic development. This systematic review of the literature focuses on the relationship between DTs and innovation. Drawing on the extant literature, we investigate 685 articles published in 41 journals from 1997 to 2023. We present the current state of different types of articles and the theoretical perspectives applied in the previous research. Based on topic modeling analyses and interpretations of existing work, we develop a meta-framework that distinguishes between the direct and indirect effects of DTs on innovation and considers four levels of potential heterogeneity affecting the relationship. Finally, we propose an agenda that emphasizes the avenues for future research on DTs and innovation.

Introduction

Innovation, which encompasses value-creating activities for stakeholders through the introduction of new products, services, business models, or procedures, is vital for organizations aiming to develop and maintain a sustainable competitive advantage in an increasingly global and competitive market (Pavitt & Walker, 1976; West & Farr, 1989). To foster and facilitate innovation, companies invest heavily in digital technologies (DTs), which most studies have considered to encompass a wide range of information and communication technologies, including artificial intelligence, robotics, digital platforms, cloud computing, 3D printing, blockchain technology, big data, the Internet of Things (IoT), virtual reality, augmented reality, and a range of new cyber technologies (Nambisan, 2017; Rindfleisch et al., 2017; Wang, 2021; Yang et al., 2021).

Organizations continuously adapt and transform their value-creation activities, organizational structures, and business models through digital transformation (Gomes et al., 2024; Nell et al., 2021). Digital transformation is "the use of new digital technologies, such as mobile, artificial intelligence, cloud, blockchain, and the Internet of things technologies, to enable major business improvements to augment customer experience, streamline operations, or create new business models" (Warner and Wäger, 2019, p. 326). The widespread adoption of DTs has been hailed as one of the most significant economic and technological developments since the Industrial Revolution (Bharadwaj et al., 2013).

Although most studies indicate that DTs have positive effects on innovation, others present a more nuanced picture, in which DTs do not always lead to improved innovation outcomes (Chatterjee et al., 2021; Ghasemaghaei et al., 2020; Park et al., 2020). Therefore, in this review, we present a balanced overview of how DTs can facilitate or stymie innovation at various levels across different domains. We consider innovation to be a broad construct that is created and deployed at different levels of analysis of the ecosystem, including the individual, firm, industry, societal, and national levels (Wang, 2021). We follow and adapt Crossan and Apaydin's (2010) definition of innovation as "the production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, markets, industries and societies; development of new methods of production; and establishment of new capabilities and management systems" (p. 1155). Thus, digital innovation can be both a process and an outcome (Hullova et al., 2016).

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Although several narrative and structured reviews on DTs and how they relate to innovation have been published, most are narrow in scope and take a reductionist approach that focuses on a specific DT or only a single level of analysis. For example, most extant reviews have considered only one type of innovation, such as Industry 4.0 or green product innovation capacity. Similarly, other scholars have used semi-structured reviews to examine the impact of DTs on new servitization business models, impact of DTs on business model innovation (Ancillai et al., 2023), and impact of Industry 4.0 DT on lean supply chain management. Other reviews have focused on specific DTs, such as artificial intelligence (AI) for firm process and social innovation (Haefner et al., 2021), social media for customer-centric innovation (Mention et al., 2019), data-driven innovation (Luo, 2022), and blockchain for innovation in business models (Tandon et al., 2022). Moreover, most of these reviews focused on the firm or industry level and fail to clarify how DTs affect innovation at the individual, societal, or national levels. Third, most reviews have highlighted the salutary influence of DTs on innovation and remain silent on how their application may not lead to improved outcomes (Chen et al., 2024).

We acknowledge that each review article advances our understanding of the relationship between DTs and innovation; however, each represents only a single piece of the complete puzzle in explaining how DTs affect and facilitate innovation at multiple levels of analysis. Thus, a more in-depth overview of the antecedents, moderators, and outcomes across multiple domains and dimensions is required (Ciarli et al., 2021). By beginning to put together the various puzzle pieces, the main objective of this review study is to offer a big-picture perspective on what we do and do not know about DTs and their impact on innovation. Because the relationship between DTs and innovation is multi-faceted and multi-dimensional, we propose a multi-level meta-framework.

With this comprehensive review, we aim to address the following research questions: 1) What are the main research topics, and to what extent do DTs play a role in the creation or facilitation of innovation at multiple levels of analysis? (2) What are the main areas worthy of investigation in future research? To address these questions, we examine 685 articles published in 41 journals between 1997 and 2023. Furthermore, we apply topic modeling to article abstracts to extract 11 research topics.

This study makes three key contributions to existing literature. First, we adopt topic modeling to analyze the relationship between DTs and innovation during the 26-year span between 1997 and 2023. The topic modeling approach is based on machine learning, and latent Dirichlet allocation (LDA) generates topics and keywords across multiple levels, summarizing key research areas. Through this analysis, we can elucidate the structure and evolution of the DT–innovation relationship over time in terms of research topics. Second, based on the results of the topic modeling algorithm and 11 research topics, we develop a meta-framework that synthesizes the ways in which various DTs can lead to a variety of innovation outcomes, as well as how they affect the innovation process at multiple levels of analysis. We also examine the direct and indirect effects of DTs on innovation and the factors that may moderate the relationship between DTs and innovation at different levels of analysis. Third, our comprehensive structured review identifies multiple opportunities for future research.

Previous reviews on DT and innovation

Several reviews on the key relationships studied here have been published. At the innovation process level, Haefner et al. (2021) conducted a review from an information processing perspective to delineate how AI and AI-based machine learning technologies can aid human decision-making in a number of areas at the front-end of the innovation process. At the firm level, another previous review examined the dialectical relationships among DTs, innovation, and skills, suggesting a new set of stylized facts that chart future trajectories of DTs, their adoption, and their effect on skill formation to drive firm innovation (Ciarli et al., 2021). Another review conduced at the firm level assessed the relationship between DTs and business model innovation and offers an interpretive framework based on four identified four cluster themes: DT-driven business model archetypes, DTs' effects on business model innovation, DT-driven business model innovation processes, and digital servitization. Using a dynamic capabilities perspective, Mention et al. (2019) reviewed the literature on how social media, as a component of DTs, leverage dynamic capabilities to drive innovation at the micro, meso, and macro levels. Based on their findings, they developed an organizational framework that illustrates how the flexible nature of social media fosters opportunities for firms to tap widely dispersed knowledge sources to enrich innovation capabilities. In a recent meta-analysis of 113 studies, Chen et al. (2024) tested the conditions under which the relationship between DTs and innovation is strongest or weakest, using a study designed at the country and industry levels to examine how these levels interact. They presented empirical evidence indicating that this relationship is stronger in countries with weak institutional support for innovation and a weak rule of law (Chen et al., 2024). Furthermore, the strength of this relationship tends to increase over time. However, they found no evidence that the strength of the relationship varies across industrial contexts or innovation paradigms. Finally, at the innovation process level, Luo (2022) synthesized the extant literature on the relationship between DTs and innovation to define AI-inspired data-driven innovation as a formal innovation process paradigm and elucidates what it entails and how it mitigates uncertainty and fosters creativity in the innovation process.

Methodology

Data collection

To achieve our study objectives, we followed the systematic review guidelines prescribed by Hanelt et al. (2021) comprising the following three steps: (1) data collection, (2) data analysis, and (3) data synthesis. We only considered peer-reviewed journals because they propagate well-validated knowledge and have the highest review standards. We used the Web of Science (WoS) database because of its broad coverage and inclusion of academic journal articles relevant to our study and it allows users to tailor their searches based on article titles, abstracts, and keywords (Tandon et al., 2021). WoS provides broad interdisciplinary coverage of various scientific fields, making it useful for reviews across the natural sciences, social sciences, and humanities. It includes prestigious citation indices such as the Science Citation Index (SCI), Social Science Citation Index (SSCI), and Arts & Humanities Citation Index (A&HCI). It also emphasizes high-quality peer-reviewed journals, ensuring that the articles included have undergone rigorous academic scrutiny, thereby supporting high standards for systematic reviews (Mongeon & Paul-Hus, 2016). According to our search criteria, only articles that included terms from both of the following search strings in titles, keywords, or abstracts were included in the sample. The first search string included the following keywords: "digit*" or "Internet of Things" or "IoT" or "artificial intelligence" or "AI" or "industry 4.0" or "mobile computing" or "cloud computing" or "social media" or "3D printing" or "4D printing" or "data analytics" or "big data" or "blockchain" or "social media" or "augmented reality" or "virtual reality" or "AR" or "VR" (Nambisan, 2017; Yang et al., 2021). The second search string included "innovat*" (e.g., innovate, innovative, and innovation), "R&D," "research and development," "research & development," "patents*," "new product development*," and "creativity" (Acar et al., 2019; Agarwal & Kapoor, 2022). Furthermore, only articles published in the FT50 (the *Financial Times'* top 50 journals), UTD24 (24 business journals selected by the University of Texas at Dallas), or 11 technology and innovation-related journals were included. This resulted in 1357 articles from 51 journals. We read various sections of each article, including the abstract, introduction, discussion, and conclusion, to screen and verify that those selected were oriented towards the mechanisms involved in revealing the impact of DTs on innovation. Finally, the number of articles was further reduced to 685 published in 41 journals between 1997 and 2023 (Fig. 1).

Although we began our effort to find articles written since 1900, the first article we found was by Liberatore and Breem (1997) on the possible influences of the adoption and implementation of digital imaging technology on banking and insurance industry innovation. Furthermore, 1900 is the earliest year available for the WoS database literature search. We included all articles written through the end of 2023, which was the endpoint of our study. Studies focusing on the principal relationship between DT and innovation have experienced an exponential surge since 2014, with 94 % of the articles in the final sample published between 2014 and 2023 (Fig. 2). As shown in Table 1, the most popular journals in our article pool are *Technological Forecasting and Social Change* (32 %) and *IEEE Transactions on Engineering Management* (15 %).

Topic modeling

Topic modeling is an unsupervised machine learning algorithm that can automatically identify latent themes in a large sample of articles (Blei et al., 2003). We adopted a neural topic model with pretrained contextualized document embeddings. This model builds on ProdLDA (Srivastava & Sutton, 2017), a state-of-the-art topic model that implements variational inference, and integrates a pre-trained bidirectional encoder representations from transformers (BERT) model. Therefore, this contextualized neural topic model consistently demonstrates significant improvements in topic coherence. Building on previous studies (Miric et al., 2023), the inputs for the LDA model were text corpora from the collected articles, including abstracts. Before feeding this text into the model, we preprocessed the data by removing stop words, stemming words to their root forms, and converting the text into a bag-of-words format, in which each document was represented as a vector of word counts. The algorithm treats each document as a mixture of several topics, and each topic is characterized by a distribution of words. By analyzing these patterns, the model groups words that frequently appear together, thereby uncovering the underlying themes within the data. Through a manual examination of each topic solution, we determined that the 11-topic solution yielded the most interpretable results. Our initial approach tested multiple models with varying numbers of topics, ranging from 3 to 20. The 11-topic model produced the highest coherence score while maintaining distinct interpretable topics relevant to our research questions. The other models either merged relevant themes or produced overly granular insufficiently distinct results. By selecting the 11-topic model, we ensured that each topic captured a specific dimension of the literature without excessive overlap, thereby providing a robust and meaningful representation of the research field. Based on the top ten keywords for each topic, the weights generated by the topic modeling algorithm, and the independent judgment and research experience of multiple innovation management researchers, we inferred 11 themes from these research topics. Table 2 presents the list of the 11 topics and keywords.

1) Digital enabled decision-making. Under this theme, scholars have investigated the effects of DTs on individuals' digital thinking or mind, cognition, and decision-making behaviors in innovation activities, as well as the innovative reshaping of work boundaries (Zirar et al., 2023). 2) Digital transformation of goods/service innovation. Drawing on processual and consequential perspectives, scholars have examined how DTs affect the innovation process and product or service outcomes (Bell et al., 2024; Wang, 2022). 3) Digital transformation of organizational capabilities. Leveraging DT to develop capabilities in big data management, real-time information capturing, and business intelligence reflects a central theme in innovation research (Füller et al., 2022). 4) Digital transformation of business models and digital platforms. Under this theme, scholars have primarily investigated how DTs facilitate business model innovation through the digital extension and enhancement of traditional business models and through the digital transformation of business models (Cennamo, 2021; Stonig et al., 2022). 5) Digital communities. The disruptive impact of DTs has altered the dynamics of collaboration and competition among enterprises, making governance and design within digital communities significant research topics (Marchegiani et al., 2022). 6) Emerging DT industry. Researchers have focused on the current state and planning of emerging industries arising from DTs (Gomber et al., 2018; Willems et al., 2017). 7) Digital transformation of traditional industries. Under this theme, the digital transformation of traditional industries, such as healthcare,

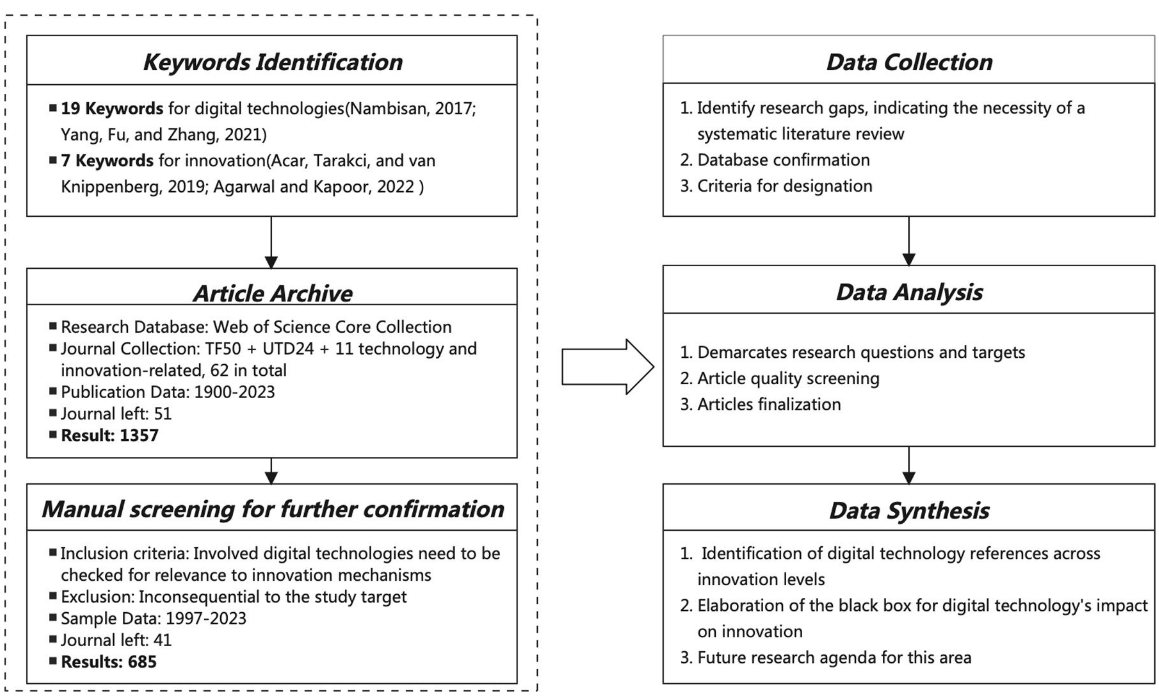

Fig. 1. Data collection process.

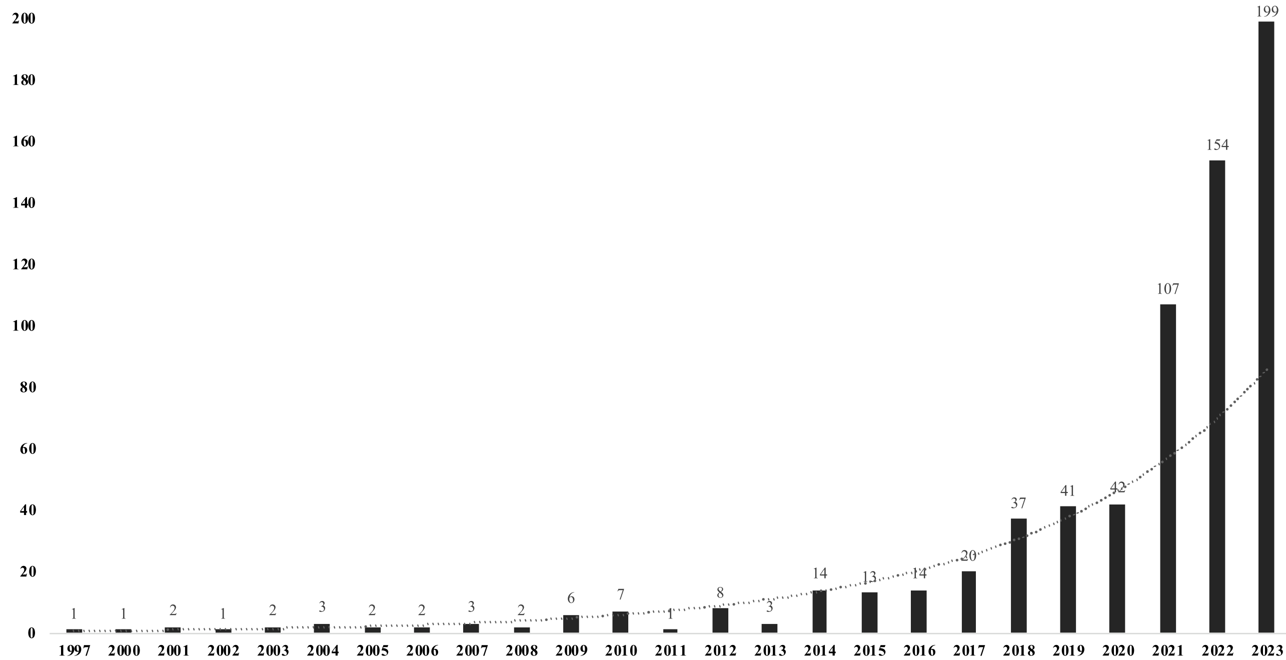

Fig. 2. Growth of publications on DTs and innovation.

transportation, and education, has emerged as a key topic in innovation research (Dozier & Montgomery, 2020; Zhou et al., 2022). 8) Digital transformation of nations. Under this theme, researchers have investigated national digital investment and policy formulation, as well as the transformation of the digital economy (Okpalaoka et al., 2023). 9) Digital sustainability. DTs can offer considerable opportunities to deliver environmental and social benefits along with sustainability (Chin et al., 2022; Halbusi et al., 2023). 10) Digital societal impact. Within this theme, scholars have focused on the impact of DTs on societal functions such as the economy, education, environmental management, and public health (Bresciani et al., 2018; Zorina & Dutton, 2021). 11) Dark side of DTs or digital transformation. Studies have focused on the tangible harm and potential risks caused by DT (Stahl et al., 2023). To show the relationships among the research topics, we plotted a network graph with exemplar keywords for each of the 11 research topics. Furthermore, we conducted citation analyses to examine how topics influence the research impact of articles, as measured by citations (Bergh et al., 2006; Vakili & McGahan, 2016). The findings show that topics 2, 3, 4, 7, 8, and 9 tend to receive more citations. Overall, we provide evidence that some topics across the firm, industry, and national levels lead to more citations than others. Therefore, we should not only review highly impactful topics but also pay attention to the less impactful topics that could shed light on future research opportunities.

Meta-framework of the DT–innovation relationship

Based on the key themes and keywords generated by the topic modeling algorithm and inspired by previous reviews, we developed a meta-framework to examine how DTs affect innovation outcomes and processes (Fig. 3). This meta-framework offers a parsimonious wide view of DT-innovation research to organize the current unwieldy literature. It builds on, but is distinct from, prior reviews in several ways. First, our review covered a longer period (26 years) than most other reviews. Second, unlike other reviews that considered one or two levels of analysis, we offer a more encompassing research design that includes individual, firm, industry, and national levels of analysis and cross-level interactions. To streamline the focus and ensure a clearer structure when discussing the different levels of analysis, we also provide a table with examples from the article pool in the last column to help readers understand the big picture and then more intuitively explore the details of the analysis (Table 3). Third, because of the comprehensiveness of our research design, we identified 11 research topics, some of which have not been covered in previous reviews. As Fig. 3 shows, the most popular research topics and categories are “digital transformation of goods/service innovation” (122 articles), “digital transformation of organizational capabilities” (132 articles), and “digital transformation of business models and digital platforms” (132 articles). Fourth, we considered the potential impact of mediators and moderators omitted from prior reviews. Fifth, we provide a broader and richer agenda for future research.

A. DT and individual-level innovation

A1. Digitally enabled decision-making at the individual level

At the individual level, DTs are critical in decision-making processes. Prior research indicates that DT integration, adoption, and deployment reflect the most useful and cost-effective way to engender innovations in the healthcare system and lead to significant improvements in health outcomes for individual patients by helping medical practitioners in decision-making (Bamel et al., 2023). Compared with human-based-approaches, DTs enable the creation of more user-centered, abductive, and iterative solutions (Verganti et al., 2020). Moreover, AI enhances managerial decision-making at each stage of the innovation process (Nell et al., 2021; Putra et al., 2024). Specifically, intelligent cognition and decision-making are required for discovering, generating, and screening new ideas, as well as experimenting with ideas, development, and commercialization (Truong & Papagiannidis, 2022).

B. DT and firm-level innovation

B1. Digital transformation of goods/service innovation at the firm level

B1.1. Facilitating the innovation process at the firm level. DT can assist firms throughout the three stages of the new product and service development process: discovering and generating new ideas, screening and experimenting with those ideas, and finally developing and

Table 1
Distribution of articles by journal outlet.

Journal title	Number of articles	Journal title	Number of articles
Technological Forecasting and Social Change	222	Journal of Operations Management	3
IEEE Transactions on Engineering Management	106	Journal of Consumer Research	3
Technovation	57	Harvard Business Review	3
Journal of Product Innovation Management	45	Strategic Management Journal	3
Research Policy	31	Marketing Science	3
International Journal of Technology Management	28	Review of Economic Studies	2
Research-Technology Management	18	Strategic Entrepreneurship Journal	2
R & D Management	16	Administrative Science Quarterly	2
MIS Quarterly	15	Human Resource Management	1
Journal of Technology Transfer	14	Human Relations	1
Industry and Innovation	14	Journal of Financial and Quantitative Analysis	1
Information Systems Research	14	Entrepreneurship Theory and Practice	1
Management Science	12	Academy of Management Review	1
Journal of Engineering and Technology Management	11	Journal of Business Venturing	1
Journal of Management Information Systems	11	Journal of International Business Studies	1
Production and Operations Management	10	Journal of Marketing Research	1
Organization Science	10	Organization Studies	1
Journal of Business Ethics	7	Quarterly Journal of Economics	1
Journal of the Academy of Marketing Science	4	Journal of Applied Psychology	1
Journal of Management Studies	4	Journal of Finance	1
Journal of Marketing	3	Sum	685

commercializing them (Brem et al., 2023). The first stage involves identifying meaningful insights or ideas that could be addressed using DT. Currently, social media are privileged vehicles that generate rich data with unprecedented multifaceted insights to drive faster ideation of client-centric innovations (Barlatier et al., 2022). Companies also use digital crowdsourcing platforms to source innovative ideas and fuel innovation efforts (Boudreau & Lakhani, 2013). Similar to Web 2.0 and social media, online 3D printing platforms facilitate the deployment of cost-effective and low-volume production units and enable firms and users to engage in (co-)creation activities. Through these practices, firms can collect and analyze information, feedback, and content from various stakeholders that provide ideas (Luo, 2022). Screening and experimentation at the second stage involve reviewing ideas, selecting the most innovative ones for further exploration, and presenting them to target customer segments to collect feedback. Machine learning may help companies explore external data and make predictions along a set of input parameters to score ideas (Truong & Papagiannidis, 2022). AI-assisted methods generate a large number of ideas at a low cost by utilizing different information sources and helping entrepreneurs screen and experiment with ideas (Bell et al., 2024). At this phase of innovation, compared with human experts, AI models have the following advantages: lower operational costs, absence of internal biases or susceptibility to adverse incentives, confidentiality without disclosure of sensitive intellectual property to third parties, and being transparent non-black boxes (Haefner et al., 2021). Once an idea is tested and validated, it enters the third stage, product development and commercialization, at which point the idea is converted into a product that can be commercialized in the marketplace. Digital design tools, such as computer-aided design and collaborative information technology, have become increasingly capable and accessible, and are creating entirely new ways to design and model systems by dramatically accelerating iteration and development concomitantly with reductions in time and cost (Marion & Fixson, 2021). In addition, 3D printing technologies are primarily used for rapid prototyping. Using DTs, market researchers can use big data gathered from social media streams, sensors embedded in consumer products, and elsewhere to identify problems with newly launched products before they escalate and develop ideas for enhancing existing products based on their observed performance. Similarly, Harz et al. (2022) identified several possible effects of virtual experimentation and simulation, virtual collaboration, big data, speed to market, and the simulation of a cradle-to-grave product lifecycle.

B1.2. Product/service innovation at the firm level. By incorporating DTs, products and services can embody inherently unbounded value-adding novelty. This product-centric perspective involves new combinations of physical and digital products to form new products or services that meet customers' latent needs. Regarding product or service categories, DT development not only upgrades the digital functions of original products or services but also directly creates emerging "smart" digital products, digital physical products, or advanced services (Porter & Heppelmann, 2014). Numerous studies have highlighted digital or digital mixed products, such as virtual reality or augmented reality-based products (Kohler et al., 2009), IoT-based products (Marinakis et al., 2021), smart products (Kahle et al., 2020), and wearable devices (Huarng et al., 2022). These studies reveal that product designers should maintain the right balance between the newness and comprehensibility of a product's meaning (Wang et al., 2022). The IoT, cloud services, and other emerging technologies allow firms to implement new forms of digitally enabled servitization (Paiola et al., 2022). In addition to firm-led service innovations, customers can play leading roles in service innovation and create value-in-use for peer consumers.

Table 2
Topics and keywords.

- Digital enabled decision making (DDM): artificial, intelligent, human, decision, learn, think, worker, behavior, cognition, attitude
- Digital transformation of goods/service innovation (DTGSI): digit, service, resource, innovation, good, creation, customer, open, transform, market
- Digital transformation of organizational capabilities (DTOC): process, capability, manufacture, collaborate, competition, structure, knowledge, routine, breadth, agile
- Digital transformation of business models and digital platforms (DTBMDP): platform, complementary, crowdfund, multiple, complementor, market, multiplatform, boundary, ecosystem, competitor
- Digital communities (DC): community, virtual, media, online, communicate, modular, social, popular, participate, member
- Emerging digital technologies industry (EDTI): analytics, technique, algorithm, scientific, criteria, methodology, forecast, visual, Python, multihome
- Digital transformation of traditional industry (DTTI): finance, cryptocurrency, security, food, patent, traceable, transparent, agriculture, medicine, farmer
- Digital transformation of nations (DTN): policy, region, economy, heterogenous, global, economic, governance, sector, expenditure, foreign
- Digital sustainability (DS): social, sustainability, open, driven, green, energy, environment, disrupt, resilience, vision
- Digital societal impacts (DSI): smart, city, IoT, network, healthcare, service, urban, infrastructure, public, security
- Dark side of digital technologies/transformation (DSDT): recover, debottleneck, terrorist, compliant, instigate, counterpoint, stringent, dampen, incident, vicissitude

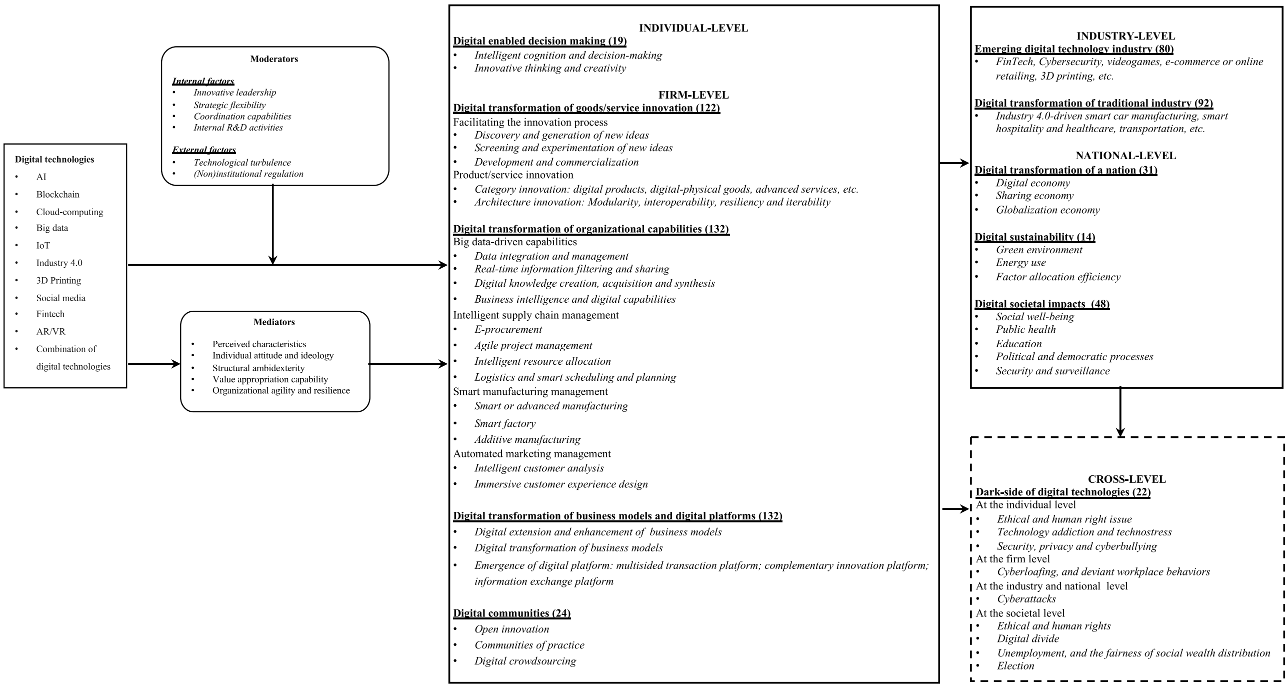

Fig. 3. Meta-framework of DTs and innovation.

Furthermore, integrating emerging technologies with products reconfigures and revitalizes the architecture or functionality of products and services, including their modularity, interoperability, resiliency, and iterability properties (Porter & Heppelmann, 2014). With the support of AI-based interactive digital platforms, smart manufacturing, and intelligent machinery (Aversa et al., 2021), manufacturing enterprises can foster innovation in iterative products by formulating guidelines for data management, integrating decision-making approaches, and establishing management standards for intelligent machines (Jiang et al., 2023). Moreover, owing to the flexible and reprogrammable nature of data analytics technologies, firms can provide individualized services to their customers (Lehrer et al., 2018).

B2. Digital transformation of organizational capabilities at the firm level

B2.1. Big data-driven capabilities at the firm level. Big data is a term that primarily describes large, unstructured, complex datasets, that require advanced and unique technologies to store, manage, analyze, and visualize. Big data and Internet-based information-sharing opportunities have enabled the creation of big data-based organizational capabilities (Huynh et al., 2023). DTs such as machine learning and big data analytics tools have enhanced firms' organizational capabilities to identify customer needs and discern trends (Mishra et al., 2022; Muhlroth & Grottke, 2022; Tambe et al., 2012). Specifically, these big data and knowledge management technologies facilitate the collection and analysis of market data to identify both customer needs and demand forecasts, which then serve as inputs in the innovation process (Chen et al., 2024). Furthermore, big data and knowledge management technologies can search, analyze, transfer, and synthesize internal and external knowledge and facilitate knowledge flows across locations within geographically disparate organizations, leading to the novel recombination of knowledge for new innovations (Forman & van Zeebroeck, 2019). Moreover, the development of AI technology has triggered the emergence, application, and deployment of business intelligence capabilities, which represent a new decision support system based on advanced information technology and techniques that goes one step further than big data analytics. It reflects the capability to collect and analyze data and convert it into information on opportunities and threats to provide intelligent solutions (Füller et al., 2022).

B2.2. Intelligent supply chain management at the firm level. DTs have profoundly changed supply chain processes (Yang et al., 2021). Conventional supply chains consist of geographically scattered physical facilities that help establish and maintain transportation links among them. Supply chain management encompasses the control, management, and enhancement of the flows of raw, semi-finished, and finished materials and information between the initial suppliers and end users through a network of organizations. A digital supply chain is an intelligent, value-driven network that leverages new approaches using DTs and analytics to create new forms of revenue and business value (Yang et al., 2021). Digital supply chain management includes interactive activities such as e-procurement, agile project management, intelligent resource allocation, logistics, and smart scheduling and planning. For example, the IoT has been deployed in factories to monitor production processes, perform quality control, and trace and track inventories, logistics, and warehousing activities (Yang et al., 2021). Real-time data collected through IoT devices and further analyzed by other DTs such as big data analytics and AI, will reveal inventory problems, optimize resource allocation, and more efficiently manage supplier relationships and outcomes, all of which fall under the umbrella of process innovation. DTs have shifted traditional supply chain management towards more data-driven approaches that yield process innovations. Evidence from a series of case studies also indicates that DTs can potentially contribute to the product innovations of a firm and its suppliers (Lee & Berente, 2012). Intelligent supply chains can also be considered a dynamic capability that enables firms to adapt to a fast-changing environment, triggering new product innovations (Teece et al., 1997).

B2.3. Smart manufacturing management at the firm level. By converging the digital and physical worlds, DTs offer flexibility in manufacturing processes to address turbulence and hyper-competitiveness in global markets (Aversa et al., 2021). Smart manufacturing is a collection of manufacturing practices that extensively utilize networked data and DTs to manage and govern manufacturing operations. This set of manufacturing practices includes smart or advanced manufacturing, smart factories, and additive manufacturing. State-of-the-art

Table 3
Summary of key articles on the impact of DTs at different innovation levels.

Innovation Level	Topics	Examples
A. DT and individual-level innovation	A1. Digital enabled decision-making	• Intelligent cognition and decision-making (Nell et al., 2021; Putra et al., 2024) • Innovative thinking and creativity (Truong & Papagiannidis, 2022)
B. DT and firm-level innovation	B1. Digital transformation of goods/service innovation at the firm level	B1.1. Facilitating the innovation process • Discovery and generation of new ideas (Barlatier et al., 2022; Boudreau & Lakhani, 2013) • Screening and experimentation of new ideas (Bell et al., 2024; Truong & Papagiannidis, 2022) • Development and commercialization (Harz et al., 2022; Marion & Fixson, 2021) B1.2. Product/service innovation • Category innovation: digital products, digital-physical goods, advanced services, etc. (Huarng et al., 2022; Kohler et al., 2009; Paiola et al., 2022; Porter & Heppelmann, 2014) • Architecture innovation: Modularity, interoperability, resiliency and iterability (Aversa et al., 2021; Jiang et al., 2023; Porter & Heppelmann, 2014)
	B2. Digital transformation of organizational capabilities at the firm level	B2.1. Big data-driven capabilities • Data integration and management (Huynh et al., 2023) • Real-time information filtering and sharing (Mishra et al., 2022; Muhlroth & Grottke, 2022) • Digital knowledge creation, acquisition, and synthesis (Forman & van Zeebroeck, 2019) • Business intelligence and digital capabilities (Füller et al., 2022) B2.2. Intelligent supply chain management • E-procurement (Yang et al., 2021) • Agile project management (Yang et al., 2021; Lee & Berente, 2012) • Intelligent resource allocation (Lee & Berente, 2012) • Logistics and smart scheduling and planning (Yang et al., 2021) B2.3. Smart manufacturing management • Smart or advanced manufacturing (Iansiti & Lakhani, 2014; Porter & Heppelmann, 2014) • Smart factories (Min,2022) • Additive manufacturing (Chen et al., 2021) B2.4. Automated marketing management • Intelligent customer analysis (Wu et al., 2019) • Immersive customer experience design (Siqin et al., 2023)
	B3. Digital transformation of business models and digital platforms at the firm level	• Digital extension and enhancement of business models (Alshawaaf & Lee, 2021; Franzò et al., 2023) • Digital transformation of business models (Chin et al., 2022; Tian et al., 2022) • Emergence of digital platforms: multisided transaction platforms; complementary innovation platforms; information exchange platforms (Gawer & Cusumano, 2014; Nambisan et al., 2018)
	B4. Digital communities at the firm level	• Open innovation (Marchegiani et al., 2022;West & Bogers, 2014) • Communities of practice (Wenger, 1998; McDermott, 2000) • Digital crowdsourcing (Acar, 2019; Afuah & Tucci, 2012)
C. DT and industry-level innovation	C1. Emerging digital technology industry at the industry level	• Fintech, Cybersecurity, videogames, e-commerce or online retailing, 3D printing, etc. (Gomber et al., 2018; Morris et al., 2020; Willems et al., 2017)
	C2. Digital transformation of traditional industry at the industry level	• Industry 4.0-driven smart manufacturing, smart hospitality and healthcare, transportation, etc. (Aversa et al., 2021; Henderson & Clark, 1990; Llopis-Albert et al., 2021)
D. DT and national-level innovation	D1. Digital transformation of a nation at the national level	• Digital economy (Brynjolfsson & Kahin, 2002; Okpalaoka, 2023) • Sharing economy (Eckhardt et al., 2019) • Globalization economy (Watanabe et al., 2003)
	D2. Digital sustainability at the national level	• Green environment (Chin et al., 2022; Halbusi et al., 2023) • Energy use (Lee et al., 2022) • Factor allocation efficiency (Gao et al., 2023)
	D3. Digital societal impacts at the national level	• Social well-being (Bresciani et al., 2018; Chang, 2021) • Public health (Browder et al., 2024; Galetsi et al., 2023; Savona, 2021) • Education (Carrasco-Farré et al., 2022) • Political and democratic processes (Zorina and Dutton, 2021) • Security and surveillance (Kumar et al., 2020)
E. Dark side of DT and digital transformation	E1. At the individual level	• Ethical and human rights issues (Vanman et al., 2018) • Technology addiction and technostress (Turel & Ferguson, 2020) • Security, privacy, and cyberbullying (D'Arcy et al., 2014)
	E2. At the firm level	• Cyberloafing and deviant workplace behaviors (Mazmanian, 2013; Khansa et al., 2017)
	E3. At the industry and national levels	• Cyberattacks (Strazzullo et al., 2023)
	E4. At the societal level	• Ethical and human rights (Stahl et al., 2023) • Digital divide (Chircu & Mahajan, 2009) • Unemployment and the fairness of social wealth distribution (Muro et al., 2017) • Elections (Robertson et al., 2021)

technologies such as the IoT, cloud computing, big data analytics, and AI have greatly stimulated the development of smart manufacturing. Smart or advanced manufacturing involves a new form of intelligent, autonomous, reconfigurable, and flexible production systems. According to previous research, manufacturing equipment that communicates with users and other machines, automated manufacturing and assembly processes that require no human intervention, and other processes that facilitate real-time communication between factories and customers are creating dynamic process innovations (Iansiti & Lakhani, 2014; Porter & Heppelmann, 2014). For example, autonomous robots may improve manufacturing system performance and material control (Liu et al., 2020). Another observed trend is the increasing adoption of smart factories. Smart factories are connected and flexible manufacturing systems that use continuous data streams from connected operations and production systems to learn and adapt to new demands. Smart factories are vertically networked and integrated with the IoT, big data analytics, cloud computing, and smart production systems. The decentralized and various components of smart factories can make autonomous decisions while remaining aligned with a single ultimate organizational goal (Min, 2022). Fundamentally, smart factor implementation can be considered a process innovation. Finally, additive manufacturing is a layer-by-layer technique for creating 3D objects directly from a digital computer-generated model and can contribute to product and process innovation in several ways. Since additive manufacturing operates based on computer-aided design modules, it can contribute not only to prototyping activities within the product development process but also serve as a production unit for customized products tailored to the specific needs of customers. 3D printing has a substitution effect of technological innovation on online demand to increase online product variety (Chen et al., 2021).

B2.4. Automated marketing management at the firm level. As marketing processes are information rich, the application of DTs can improve marketing tools and enhance activities to create, communicate, and deliver offerings that are valuable to customers, clients, and partners in global markets. First, concerning intelligent customer analysis, the industrial IoT enables the real-time acquisition of market data, big data analytics analyzes and visualizes data, and cloud computing provides data storage and structuring. These technologies support real-time marketing decision-making and enable more accurate and intelligent customer profiling and forecasting (Wu et al., 2019). Using big data, companies can obtain online consumer review information to enhance marketing predictions, explore consumer preferences for product features, and predict the effectiveness of product trends (Siqin et al., 2023), thereby contributing to incremental and next-generation product and service innovations. Second, regarding the user experience design, DTs can introduce highly realistic and immersive customer experiences into multiple user touchpoint scenarios. For examine, as part of augmented reality that integrates computer-generated objects into a physical environment, haptic rendering technology has generated interfaces that provide the sensation of actual touch when exploring online environments for service innovation.

B3. Digital transformation of business models and digital platforms at the firm level

A business model is “a well-specified system of interdependent structures, activities, and processes a firm’s organizing logic for value creation (for its customers) and value appropriation (for itself and its partners)” (Sorescu et al., 2011). The use of DT-enabled changes to structures, activities, and processes leads to the definition of digital business model innovation (Sorescu et al., 2011). A significant literature stream focuses on how firms can transform their business models in various ways (Ancillai et al., 2023). Digital business model innovation can be viewed as organizational innovation. Researchers have developed a taxonomy of digital business model innovation in five major research areas. The first research area aims to develop a taxonomy of digital business model innovation comprising a spectrum of changes in value creation, delivery, and capture. The second research area focuses on native digital business models such as the freemium model, digital platforms, and the SAAS business model. The third area examines how DTs affect and serve as antecedents of business model innovation and drive changes that affect certain business model components. The fourth area elucidates how DTs can adopt process-based logic to drive business model innovation. The last research area examines the digital servitization of business models, which is the process of adding services to a product-centric business model (Paiola et al., 2022).

Fundamentally, DTs primarily facilitate business model innovation through digital extension and enhancement or system-wide digital transformation of a firm’s current business model. First, the digital extension and enhancement of a current business model refers to a firm’s use of DTs to support new business processes in one or more components of its business model (Alshawaaf & Lee, 2021). These new processes complement existing activities and workflows to advance new products and pursue new customers, such as digital piracy (Aversa et al., 2019). Firms can exploit DTs to improve their value-creation, delivery, and appropriation mechanisms through redesigning infrastructure management, product pillars, customer interfaces, and financial aspects (Franzò et al., 2023). DTs enable firms to develop new or enhanced value-creation opportunities and customers to improve their consumption and usage experiences, culminating in both product and service innovations (Cheng & Wang, 2022).

Second, the system-wide digital transformation of a business model refers to the wholesale development of new business models using DT to replace traditional ones. Chin et al. (2022) found that the application of blockchain technology is likely to disrupt the established collaboration and coordination procedures adopted by participants in existing business models, as it reshapes the traditional technological infrastructure and associated value chain systems. Consequently, firms can leverage blockchain technology to transform traditional business model structures into more innovative, digitized, and complex platforms. Tian et al. (2022) showed that manufacturers can gradually move along the product–service continuum, using Industry 4.0 technology to move from a non-digital servitization position to a fully digital one and achieve smart servitization.

Furthermore, many industries and firms are undergoing platformization, which refers to a shift from individual products and services sold through traditional supply and distribution chains to platforms that serve as intermediaries for transactions and organizing value-creation activities (Gawer, 2014). Digital platforms are defined as the layered architecture of DT that orchestrate and integrate software, hardware, operations, and networks (Yoo et al., 2010) to facilitate interactions between different user groups (Cennamo, 2021; Gawer, 2022). Specifically, multisided transaction platforms (e.g., e-commerce, B2B, and online labor platforms) directly connect sellers and buyers and facilitate value-exchange transactions among them.

In addition to enabling interactions between different sets of users, digital platforms can facilitate innovation (Nambisan et al., 2018). For example, digital platforms provide an outlet for third-party firms, such as software developers or other service providers, to develop and offer complementary products (e.g., video games) or services (e.g., transportation and accommodation) (Gawer & Cusumano, 2014). In the mobile context, digital platforms (e.g., Android Play Store or Apple App Store) facilitate the development of millions of applications for mobile device users.

B4. Digital communities at the firm level

An increasing number of firms, especially technology-based ones, are utilizing digital communities by embracing open innovation as part of their innovation strategies. Pervasive DT use has challenged traditional innovation processes in that innovation agency is no longer centralized (Marchegiani et al., 2022). Consequently, open innovation processes enable the spread of control over knowledge creation, sharing, and innovation across multiple individuals and organizations (Mahr & Lievens, 2012; Shaikh & Levina, 2019). A significant literature stream has developed on specific forms of digital communities such as (open) innovation (Chesbrough et al., 2006), communities of practice (Wasko & Faraj, 2005), digital crowdsourcing (Afuah & Tucci, 2012; Bayus, 2013), and knowledge exchange communities (Faraj et al., 2011), and how these communities can contribute to different aspects of the innovation process. Several studies have examined how digital communities can contribute to open innovation.

Open innovation refers to “the use of purposive inflows and outflows of knowledge to accelerate internal innovation and to expand the markets for external use of innovation, respectively” (Chesbrough et al., 2006, p. 1). Several studies have demonstrated the role of external sources on innovation outcomes (West & Bogers, 2014). Other studies have adopted an open innovation perspective to examine innovation processes. For example Marchegiani et al. (2022) investigated distinct knowledge collaboration among firms in digital communities, a key activity in the innovation process, while Mulhuijzen and De Jong (2024) found that including professionals in online user innovation communities, which are a specific form of digital community, enhances the diffusion of user innovations relative to the inclusion of amateur users.

Another form of digital community is a community of practice. Communities of practice are groups of individuals who share information, knowledge, insights, and tools related to a specific discipline, technology, or skill. These communities are an efficient, low-cost approach to enhance innovation with the primary objective of exchanging knowledge, approaches, and solutions. Firms involved in dispersed collaborations and communities of practice have better front-end innovation performance than firms that are not.

Crowdsourcing is a third form of digital community and refers to the activity of opening up an organizational challenge to a large external crowd, typically via the Internet (Afuah & Tucci, 2012). Recent evidence has indicated that participants' different motivations on digital crowdsourcing platforms can relate to the appropriateness of innovations in various ways (Acar, 2019). Furthermore, the effects of positive peer feedback when using field data secured from an idea-crowdsourcing community enhance subsequent idea quality as ideators gain experience (Chan et al., 2021).

C. DT and industry-level innovation

C1. Emerging DT at the industry level

Widespread DT use has also led to the emergence of new industries, such as fintech, cybersecurity, and videogaming. The IoT, big data, cloud computing platforms, blockchain, and other cyber-physical systems have fundamentally driven innovations and the development of fintech (Gomber et al., 2018), e-commerce or online retailing (Willems et al., 2017), and 3D printing (Rayna & Striukova, 2016). For example, the fintech industry is populated by startups that create value by introducing new DT-powered innovations such as rapid payment systems, cryptocurrencies, blockchain applications, and cross-border payment systems (Gomber et al., 2018). Similarly, the cybersecurity industry has emerged to offer innovations that protect proprietary information, maintain the integrity of databases, offer authorized users timely access to information systems, and prevent unauthorized access and damage to information technology infrastructure (Morris et al., 2020).

C2. Digital transformation of traditional industry at the industry level

The digital transformation of traditional industries, such as the transformation from traditional automotive manufacturing to Industry 4.0-driven smart car manufacturing (Llopis-Albert et al., 2021), has triggered a shift in product (Henderson & Clark, 1990) and industry architecture (Jacobides et al., 2006), thereby affecting how value is created and captured (Teece, 2018). Traditional industries typically design new products based on modular architecture, as presented in a single value proposition, and profit from innovation by controlling complementary assets (Teece, 1986; 2007; 2018). After the digital transformation of an industry, new products and services as well as new strategic category priming (Aversa et al., 2021) are designed around a stack of technologies, also known as a layered modular architecture (Bohnsack et al., 2021). Moreover, the application of DTs and data resources resulting the digital transformation of traditional industries yields an increase in output and efficiency. The transformation and development of the automobile industry have ushered in a new era of intelligence and connectivity, as DTs have gradually been integrated into products and the production process (Zhou et al., 2022). For example, DTs in account for at least 50 % of a new vehicle's total value (Llopis-Albert et al., 2021). The confluence of software and hardware embedded in new vehicles has enhanced not only their functionality and versatility but also their complexity. In the healthcare industry, traditional medical records and documents are stored in the cloud to allow doctors to immediately access to patient data anywhere. In supply chain management, Maersk operates a blockchain-based system to trace container shipping.

D. DT and national-level innovation

D1. Digital transformation at the national level

The first examines how DTs can contribute to and enable a nation's digital transformation. The important role that products and services enabled by information and communication technology have come to play in modern economies has given birth to the idea of the "digital economy" (Brynjolfsson & Kahin, 2002). Emerging DTs have played critical roles in the development of the digital economy (Okpalaoka, 2023), sharing economy (Eckhardt et al., 2019), and globalizing economy (Watanabe et al., 2003). Digital products or online and virtual services are the predominant forms of innovation developed in digitally transformed nations and are the result of other DTs that have enabled the digitization of audio, visual, and textual information (Sorescu & Schreier, 2021). The digitization of a wide range of products and services has led to the revitalization and renewal of many services (e.g., music and video distribution), creation of entirely new services (e.g., cloud computing, SAAS, and digital movies), and decline of other industries (e.g., newspapers and book publishing) (Elberse, 2010; Hennig-Thurau et al., 2007; Pattabhiramaiah et al., 2019). Some nations have adopted digital government platforms to stimulate service innovation, whereas others have examined how digital governments can foster regional eco-innovation through formal and informal environmental regulations (Zhao et al., 2023).

D2. Digital sustainability at the national level

Data unavailability and integration often impedes the move towards a more sustainable world and a circular economy (Chauhan et al., 2022). Therefore, sustainability and the quest towards a circular economy and digital transformation are inextricably linked (Bag et al., 2021). For example, blockchain, big data analytics, and AI can facilitate new means of green and circular production and innovation, in addition to monitoring and storing data on activities responsible for pollution and environmental degradation (Chin et al., 2022; Halbusi et al., 2023). Similarly, industrial robots are a major process innovation that can reduce the energy usage required for manufacturing activities and have positive environmental effects (Lee et al., 2022). Industrial robot technology enables efficient production resource allocation, reduces waste by acquiring timely and pertinent production information and knowledge, and saves energy through green processes and product innovations. Big data improves green innovation in the manufacturing industry by improving the factor allocation efficiency for both labor and capital (Gao et al., 2023).

D3. Digital societal impacts at the national level

A sub-stream of the literature on the relationship between DTs and innovation has attempted to elucidate the societal impact of DT-enabled innovations (Carrasco-Farré et al., 2022). This impact is varied and profound in the areas of social wellbeing, public health, education, political and democratic processes, and security and surveillance. Prior research has investigated how DTs can be deployed to create innovations that provide value to the broad swath of society during crises such as the COVID-19 pandemic (Browder et al., 2024; Galetsi et al., 2023; Savona, 2021). Furthermore, AI could have an important societal impact on crisis response, economic empowerment, educational challenges, carbon-neutral challenges, equality and inclusion, health and hunger, information verification and validation, infrastructure management, public and social sector management, and security and justice (Zorina & Dutton, 2021). The dense innovation ecosystem that creates value through the use and reuse of information is facilitating the development of smart cities by designing local areas using new information and communication technologies such as the semantic web, cloud computing, mobile devices, and the IoT (Bresciani et al., 2018; Chang, 2021). Smart cities leverage the intelligence of a city's community and assume a relevant role as innovation drivers (Kumar et al., 2020).

E. Dark side of DTs and digital transformation

The proliferation of DTs and the innovations to which they contribute can be a "force for good" and facilitate the achievement of grand challenges (Murray et al., 2012). However, DTs may also create innovations that cause harm at individual, firm, and national levels.

E1. At the individual level

The relationship between DTs and innovation has yielded insights into challenges, including the excessive use of DT-enabled innovations such as violent video games, phishing apps, stalkerware, fake dating apps, gambling apps, and chatbots that spread misinformation. Furthermore, DT-enabled innovations can lead to technology addiction (Turel & Ferguson, 2020), overload anxiety (Vanman et al., 2018), adverse health outcomes, security and privacy concerns (D'Arcy et al., 2014), cyberbullying, and the dark side of user-generated content. A key example is how AI technology led to the creation of ChatGPT, an innovation with several drawbacks such as its provision of inaccurate or false information and its ability to generate deceptive content, impersonate individuals, or conduct social engineering attacks, as well as the possibility users could become dependent on such tools or lose skills such as analytical reasoning.

E2. At the firm level

Digital apps that enable employees' constant connectivity to work (Mazmanian, 2013), cyberloafing (Khansa et al., 2017), deviant workplace behavior (Turel, 2017), and reduced control over work can negatively affect productivity and innovation. Furthermore, firms spend significant resources on protecting themselves against threats such as cyberattacks (Kamiya et al., 2021) and industrial espionage.

E3. At the industry and national level

A cyberattack directed at companies using Industry 4.0 technology can have disastrous effects, leading to product deterioration, destroyed systems and devices, production downtime, and consequent financial and reputational losses (Strazzullo et al., 2023).

E4. At the societal level

DT can lead to innovations that result in the loss or displacement of jobs due to large-scale automation (Muro et al., 2017), bad practices in e-commerce, and the quasi-monopolistic positions of digital platforms. Furthermore, some DTs can be converted into innovations that undermine ethical and human rights, such as data privacy; bias and discrimination related to gender, race, and age; protection rules; and safety and security (Stahl et al., 2023). The opacity of AI-based innovations leads to concerns about hidden biases and resulting unfair discrimination. These limitations make AI innovations a dangerous tool if knowledge is fully embedded into neural networks, and AI users are unable to derive the logic underlying suggested decisions (Lepore et al., 2023).

In addition to the potential issues arising from the nature of DTs, numerous concerns have been voiced regarding their roles within larger socio-technical systems and the potential impact this may have on individuals, organizations, and nations. The application of DTs will give rise to issues such as the digital divide, which reflects the differences among countries and regions in terms of DT utilization, technology accessibility, economic level, and government support. With this understanding, national governments have greater potential to plan and stimulate productive DT use (Chircu & Mahajan, 2009). AI is expected to have a significant economic impact, raising issues concerning unemployment, worker surveillance, and the fairness of social wealth distribution (Hassard & Morris, 2022). Big data analytics and AI can influence political processes, lead to a concentration of power, and undermine democracy through election forecasting, campaign management, and political risk assessment. DTs also have the potential to change the nature of warfare, including alterations in the boundaries of capabilities such as reconnaissance, intelligence, surveillance, target acquisition, precision control, guidance, cybersecurity, survivability, mobility, and lethality, thereby constructing the scope of human actions in adverse ways (Robertson et al., 2021).

F. Moderators of the relationship between DT and innovation

The literature has explored numerous internal and external moderators that influence the relationship between DTs and innovation. For example, studies have identified key internal moderators such as innovative leadership (Bag et al., 2021; Reuter & Floyd, 2024), strategic flexibility (Li & Wang, 2023; Shi et al., 2023), coordination capabilities (Candi & Beltagui, 2019), and research and development activities (Radicic & Petković, 2023). Prior research suggests that organizational enablers constitute a crucial moderating factor in the DT–innovation relationship, while organizational context and technology demonstrate strong interdependence (Troilo et al., 2017). Innovative leadership (Bag et al., 2021) has shown a crucial role in enhancing the impact of big data analytics on healthcare supply chain innovation, responsiveness, and resilience, particularly during the COVID-19 pandemic (Browder et al., 2024; Savona, 2021). Li and Wang (2023) showed how DT investments affect different types of innovation, focusing on two dimensions of strategic flexibility: resource and coordination flexibility. Their findings revealed that resource flexibility can dilute the positive link between DT investment and exploitative innovation because of its substitution effect. Conversely, both resource and coordination flexibility amplify the association between DT investment and exploratory innovation, indicating a reinforcing effect of DT on innovation. Shi et al. (2023) highlighted that organizational agility can significantly enhance the abovementioned relationships between DT adoption and vertical and horizontal collaborative innovations in China's high-speed rail industry.

Moreover, external factors that affect the relationship between DT and innovation explored in the literature include technological turbulence (Candi & Beltagui, 2019) and (non)institutional regulation (Lee et al., 2022; Zhao et al., 2023). For example, Candi and Beltagui (2019) offered insights into how technological turbulence affects the use of 3D printing for product innovation, observing that technological turbulence positively moderates the relationship between the use of 3D printing in innovation and innovation performance. Regulatory frameworks, including formal and informal regulations, also significantly influence this relationship. Lee et al. (2022) showed that strong environmental regulations positively moderate the relationship between industrial robot applications and green technology innovation in manufacturing. Similarly, Zhao et al. (2023) investigated the effects of informal environmental regulation and found that it positively moderates the impact of digital administration on regional eco-innovation and enhances the relationship between digital citizenship and regional eco-innovation. Liu et al. (2023) suggested that an intellectual property rights protection system negatively moderates the relationship between DT adoption and innovation speed, as well as operational efficiency.

Future avenues for research

Based on our comprehensive review of the relationship between DTs and innovation, we propose several avenues for future research for each of the topic clusters identified above. Based on our meta-framework in Fig. 1, we observe that significant future research opportunities are present in all topic clusters, especially in the literature streams at the individual-, national-, and cross-level analyses. Moreover, we examined the topic network x to identify potential gaps among various topics and keywords that could be reconnected with new links. These new links can clarify the interactions between different topics and levels and offer avenues for future research.

Future research avenue 1: digital enabled decision-making

DTs such as cloud and edge computing, machine learning, advanced AI, and the IoT are known to disrupt human perception, with previous studies mainly focusing on human perception barriers (Mani & Chouk, 2018) and intelligent decision-making (Pietronudo et al., 2022). Considering this, future research should focus on how the broadening of human perception can contribute to algorithmic thinking and drive creative breakthroughs. Another area for future research is investigating how DTs in general and AI technologies in particular affect decision processes in organizations, which may lead to improvements or augmentation in perceptions to assist in the creation of innovations. For example, studies could explore the appropriate balance of automated, augmented, and human decision-making in driving innovative thinking in marketing and branding, strategy formulation, capability development, operations, and supply chain strategy at the highest level of the organization, such as the CEO or top-management-team level. Our topic network also confirms that there are few existing connections or a lack of research between digitally enabled decision-making at the individual level and the digital transformation of organizational capabilities at the firm level. Furthermore, since DTs frequently mediate leadership behaviors and managerial practices (Leonardi et al., 2012; Reuter & Floyd, 2024), we recommend that future research elucidate the use of DT by leaders (e.g., CEOs) as a special type of end user and examine how DTs and different DT combinations may lead to novel work designs or managerial practices. In a digital platform context, Parker et al. (2017) noted that DTs can change or modify knowledge, skills, motivations, and perceived opportunities and may lead to innovations in work design and managerial practices for better adaptation to a digital environment. Other issues to be addressed in this research stream include how DTs affect the tasks in the innovation process, what new individual competences are needed in cross-functional NPD teams, how digital cognition affects the human–machine relationship.

Future research avenue 2: digital transformation of goods/service innovation

DTs and AI-driven applications can be used for information searches, idea generation, and value creation. At the frontend of the innovation process (Brem et al., 2023), during the ideation phase, AI tools could potentially augment human decision-making in four areas (Haefner et al., 2021): (1) scanning information spaces and identifying ideas by overcoming information processing constraints, (2) generating ideas by overcoming information processing constraints, (3) developing ideas by overcoming local search routines, and (4) generating and combining ideas by overcoming local search routines. How innovation managers can use tools such as reinforcement learning, deep learning, and machine learning for each of these tasks, and what the extent of human intervention should be, remain unclear. Furthermore, how organizations can best acquire and organize the skills necessary to perform these tasks requires further exploration Another important area for future research is examining several competing machine/deep learning approaches to identify the best fit at different stages in the innovation process across various product and service categories. This research will require interdisciplinary approaches. Finally, different DT configurations and their impact on individual innovation, innovative thinking, and innovative processes have great potential for future studies. For example, researchers can envision how AI tools, in conjunction with IoT and social media, can lead to new approaches for accomplishing tasks or solving problems.

Further down the innovation funnel, at the backend of the innovation process, AI tools and big data analytics can assist in feature selection for a chosen idea and user feedback. Future research should examine these poorly understood processes and compare them with traditional human-driven processes of feature selection and obtaining, analyzing, and acting on user feedback. As AI tools combined with rapid prototyping tools such as 3D printing may lead to new designs, research should investigate whether these are more successful than those created by humans.

Several questions regarding how digital innovations come into being based on the building blocks of DTs remain unanswered (Lyytinen et al., 2016; Nambisan, 2013). Nambisan et al. (2017) posited that the traditional segregation between innovation processes and outcomes is no longer valid in the digital age, calling for future research to examine the specific nature and dynamics of both. Researchers have taken the first step in this direction by showing how digital tools and technologies such as minimum viable products and wireframes are part of both innovation processes and outcomes (Pershina et al., 2019).

Future research avenue 3: digital transformation of organizational capabilities

This topic cluster provides several opportunities for future research. For example, digitally transforming emerging organizational capabilities and turning them into dynamic capabilities in new ventures is an important area for exploration (Autio et al., 2018; Huang et al., 2017). Of critical importance in this research stream is the elucidation of the sources of competitive advantage in all types of companies because the extensive use of DT creates a high level of opaqueness (Brem et al., 2023) which, consequently, shrouds the real sources in uncertainty (McGrath, 2013). Therefore, future research must explore the temporal role of DTs, the transformation that they enable for organizational capabilities, and the link to the sustainability of competitive advantage. Future research may also need to focus on single organizational capabilities for digital transformation, what DTs are most appropriate, and how organizations can systematically and appropriately develop and transform a particular capability. Specifically, future research could synthesize the organizational capability and digital maturity model literature. Researchers should focus on the company itself as the target entity and call for studies on digital maturity models of organizations with an emphasis on the digital transformation of its processes, products/services, and business models.

Most studies on the digital transformation of organizational capabilities focus on organizational-level capabilities. Thus, research provides little insight into how employee-level individual competencies can aggregate and give rise to organization-level capabilities. Previous studies have identified individual competencies that explain heterogeneity in organizational capabilities (Rothaermel & Hess, 2007), suggesting that future research on the digital transformation of individual competencies should be linked to that of organizational capabilities.

Future research avenue 4: digital transformation of business models and digital platforms

We structure the discussion on future research on business model digitalization based on three key functions:1) value creation, 2) value delivery and 3) value capture. With respect to value creation, how combinations of DTs, such as digital fabrication and Web 3.0, lead to new means of value (co-)creation remains an open question. In addition, further insights are critically needed into the role of single and configurations of DTs and how they can enhance or create new value propositions. For example, value creation should be examined from the perspective of how customer data generated by AI tools and social media can enhance or create entirely new value-creation processes. Because value is frequently created in a digital ecosystem context, future research may examine how different ecosystem configurations may create different degrees of competitive advantage.

With regards to value delivery, future research could examine how a full set of DTs can achieve service innovations. The IoT, big data analytics, and cloud computing are among the most disruptive technologies for service innovation, and the role of other technologies, such as AI, augmented reality, and additive manufacturing, requires more exploration (Porter & Heppelmann, 2014). Future research should investigate the optimal configurations of DTs to create and deliver new services.

Furthermore, more exploration is needed around a better understanding of the value capture of ecosystems of business models (Teece, 2018). For manufacturing firms in the digital era, how and under what conditions investment in DTs leads to value capture between manufacturers and distributors requires further investigation. Future research should adopt longitudinal designs to explore how revenue models evolve along the lifecycle of product-centric service companies.

Future research avenue 5: digital communities

As more companies realize the benefits (and challenges) of being involved in digital communities to enhance their innovation processes or outcomes (Fisher, 2019), several areas fertile for future research are emerging. A fruitful area revolves around the development of measures of involvement in digital communities and how they can fuel innovation. Similarly, future research can gauge how a company's involvement in multiple different digital communities drives innovation efforts and how their unique effects can be measured. Researchers should explore whether it is better for firms to create their own digital communities or to leverage existing communities, and under what conditions this can lead to innovations with the most impact. Digital crowdsourcing platforms are a type of digital community that sources ideas or funding to facilitate innovation processes or fuel innovations. Future research should examine the development of measures or metrics to gauge the value of crowdsourcing in innovation processes and outcomes. Other studies can explore the extent to which innovation quality depends on the type of incentives provided to address a problem (Afuah & Tucci, 2012).

Future research avenue 6: emerging DT industries

More research is needed on the relationship between DTs and their relationship to the emergence of entirely new industries, representing innovation at the industry level. Several issues can be addressed in future studies, such as how firms in emerging DT industries influence co-development and co-creation with other companies and companies up and down the value chain and those in traditional industries. Future studies can also examine how dominant designs develop in emerging digital industries, as well as how emerging DT industries interact and coevolve with traditional industries.

Future research avenue 7: digital transformation of traditional industries

From a theoretical perspective, existing theoretical lenses can be deployed (Hanelt et al., 2021) and new theories should be developed in the DT age with the advent of new actors and constellations that may facilitate, threaten, replace, or complement existing rules in digitally transformed traditional industries. Future research should conduct industry-wide surveys to examine the factors that influence the decision to invest in DTs to develop new products, processes, or organizational innovations, as the payoff in these investments is uncertain. Other pertinent research topics for future studies include how can small and medium-sized enterprises operating in traditional industries can leverage DTs in the innovation processes available within or outside their industries. Research is also needed on the roles of IoT, AI technologies, and cloud computing in reducing the barriers to accessing indispensable assets in the NPD process. Studies should also determine the extent to which innovation ecosystems in traditional industries accelerate the digital transformation of small and medium-sized enterprises and larger companies, as well as can start-ups can foster, accelerate, and contribute to large companies' DT use to fuel innovation.

Future studies should also examine sectoral differences in the uptake and development of DT-enabled technological capabilities and how they can enhance both innovation processes and outcomes. In addition, more insights are needed to into how the accumulation of DT-based technological capabilities or lack thereof in low- and medium-technology sectors can either widen or close the innovation gap in high-tech sectors. Future studies should focus on skills, knowledge, learning mechanisms, and systemic actors that play a role in the digital transformation process driving innovations (Peerally et al., 2022).

Future research avenue 8: digital transformation of nations

A body of literature has emerged on the sharing economy, which represents a significant and growing portion of a nation's economy across industries as diverse as transportation, lodging, clothing, financial services, food services, and office space (Eckhardt et al., 2019). These products and services are delivered through platform-mediated ecosystems. Future research should examine topics such as whether the sharing economy creates well-being to induce innovation and if the sharing economy cam develop innovations that reduce inequality. Firms and distribution channels in a blockchain-based sharing economy alter how firm assets can be managed and innovation processes can be optimized for effectiveness and efficiency. Therefore, future research should examine how asset transparency and enhanced trust affect how assets are managed and deployed for innovation. From a methodological perspective, techniques should be identified that allow scholars to access empirical blockchain data from manufacturing and distribution operations to study the efficiency of innovative processes.

Future research avenue 9: digital sustainability

The relationship between DTs and sustainable innovation can be examined at multiple levels. For example, a deeper understanding is needed regarding the positive and negative effects of DTs on sustainable innovation and whether the use and adoption of DTs facilitate convergence of the dual objectives of sustainability and financial performance. Future studies can also attempt to identify the disadvantages and limitations of DTs in the innovation process for sustainable products and services and in what industries is the relationship between DT and sustainable innovation is strongest or weakest. Furthermore, studies should explore configurations of DTs, such as big data, social media, AI tools, or the IoT, to maximize the success of sustainable innovations. Future studies could also adopt a meta-analytic approach to offer more conclusive evidence on the role of contextual specificities between DTs and sustainable innovations across industries and geographies. In addition, more scholarly work is needed on the relationship between DT and circular economy, a novel organizational innovation that does away with the "end-of-life" approach of products and services and replaces it with the "cradle-to-cradle" approach by effectively using DTs (Chauhan et al., 2022).

Future research avenue 10: societal impact of DTs

Different nations have various interpretations of the data generated by DTs. In the US, data are considered an asset that can be commercially exploited and platforms, allowing companies such as Amazon, Uber, and Tesla to profit from the data collected to develop innovations (Cusumano et al., 2019). In China, data are a public good, and digital platforms are asked to collect data that serve the state, often at the expense of profitable innovations. In European countries, data privacy is considered an individual right that requires protection, and as such, resulting innovations are defensive and reactive to regulations. Future studies should assess how these different views may affect innovation.

Furthermore, the labor force needs to be digitally transformed to fuel all types of innovation. Therefore, researchers should explore the potential impact of DTs on workers' creativity potential and experimentation skills in the innovation process, as well as the impact of DT on the working conditions of those involved in this process. Future studies are also needed to identify the tasks in the innovation process that are best performed by DTs and those that are better conducted by humans. The new worker tasks that will emerge to complement DTs in the development of new product and service innovations must also be identified. Some workers will be displaced because AI will automate their tasks away. Therefore, research must address how these workers can be redeployed in other industries where their skills will be valuable in innovation.

Future research avenue 11: dark side of DT

Several research gaps exist for this topic cluster, as most of the icebergs that represent the dark side of DTs remain submerged. From a methodological perspective, beyond focusing on pure survey data, future studies should adopt longitudinal research designs, large-scale randomized controlled trials, and experiments to assess how the feelings and perceptions of DT users are aware of and deal with DT-enabled innovations with profound adverse side effects. More research is required on what motivates individuals and firms to use DTs to develop harmful innovations such as hacker software, digital ransom apps, cyberbullying, and gambling apps. Future research can also explore the product features responsible for adverse effects and how these can be redesigned to minimize the harm inflicted on users. Further research could also explore the unauthorized use of data obtained through the IoT or social media for the development of new innovations. Overall, more research is needed on the mitigation mechanisms that could be deployed to cope with the negative impact of harmful DT-enabled innovations.

Future research avenue 12: contextual mechanisms

Future research should explore the moderating impact of national culture on the DT–innovation relationship, as culture may affect DT adoption rates and thus innovations enabled or produced by DTs (Steers et al., 2008). Similarly, more insights are needed into how DTs shape organizational culture and all types of innovation. Future studies could also assess the moderating effects of industry, competitive intensity, environmental dynamism, market turbulence, and firm size on the principal relationships studied. At the firm level, different leadership styles may affect how DTs will lead to innovations at various levels.

Limitations and suggestions for future reviews

As with any other study, this review has several limitations. First, although we focused on how DT affects various domain innovations across multiple levels, we did not consider the process level of analysis, which is important because innovation is a process. For example, the digital innovation process may involve various steps including initiation, development, implementation, exploitation, outcomes, and feedback, with each step requiring different resources, structures, routines, and performance evaluations. Future reviews could investigate the different (sub)-processes of digital innovation processes. Furthermore, a more comprehensive treatment of various institution-related moderators can be considered, such as cultures and the rule of law (Chen et al., 2024). Another limitation relates to the number of mediators considered. For example, several attributes of the top management team and employee skills can serve as important mediators in converting DT into various innovations.

Conclusion

This review aimed to unravel the intellectual structure of the literature focusing on the relationship between DTs and innovation at multiple levels of analysis by employing topic modeling. The literature is currently fragmented, growing unwieldy in different directions, and spreading across a vast range of specialized journals in various disciplines. This study contributes to the literature by offering a comprehensive meta-framework that reviews literature at multiple levels of analysis. We identified 11 distinct topic clusters in the literature that present opportunities for further research. Moreover, we briefly summarized the policy implications of the topics identified in our analysis.

CRediT authorship contribution statement

Hao Jiao: Data curation. **Tang Wang:** Writing – original draft. **Dirk Libaers:** Conceptualization. **Jifeng Yang:** Methodology. **Lingshu Hu:** Visualization, Software.

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