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Understanding digital transformation in advanced manufacturing and engineering: A bibliometric analysis, topic modeling and research trend discovery

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ABSTRACT

Digital transformation (DT) is the process of combining digital technologies with sound business models to generate great value for enterprises. DT intertwines with customer requirements, domain knowledge, and theoretical and empirical insights for value propagations. Studies of DT are growing rapidly and heterogeneously, covering the aspects of product design, engineering, production, and life-cycle management due to the fast and market-driven industrial development under Industry 4.0. Our work addresses the challenge of understanding DT trends by presenting a machine learning (ML) approach for topic modeling to review and analyze advanced DT technology research and development. A systematic review process is developed based on the comprehensive DT in manufacturing systems and engineering literature (i.e., 99 articles). Six dominant topics are identified, namely smart factory, sustainability and product-service systems, construction digital transformation, public infrastructure-centric digital transformation, techno-centric digital transformation, and business model-centric digital transformation. The study also contributes to adopting and demonstrating the ML-based topic modeling for intelligent and systematic bibliometric analysis, particularly for unveiling advanced engineering research trends through domain literature.

1. Introduction

Cross-border integration, innovation, and transformation have become industrial development themes in the digital economy era. In recent years, digital transformation (commonly abbreviated to DT or DX) has drawn attention from its critics as a new momentum and driver for economy-raising in the digital economy era. DT is "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" [1]. The four essential elements of DT are 1) target entity (i.e., the organization that adopts DT); 2) scope and focus of the transformation; 3) technology adoption and manners; and 4) contexts and benefit goals of the expected change [1,2]. If an organization undergoes DT, it is said to be "triggering significant changes and effectiveness to its external market strategy and internal organization tactics through combinations of information, computing, communication, and connectivity technologies" [1,3,4]. An organization with a high DT maturity means that it can upgrade and transform in different aspects like operational processes, value proposition, customer experience, and culture while being market sensitive at the same time [1,3,5]. In doing so, organizations have changed the perception of customer value and experience simultaneously [3,4,6]. To fully reap the benefits of DT, an appropriate DT strategy is necessary. DT must be successfully integrated into organizations to obtain sustainable competitiveness so that "design and management of DT" are essential [1,7]. This can be achieved by integrating the organization's resources and business requirements to design unique, innovative value solutions tailored to the organization's circumstances at any given time [8,9]. In industries where there is less interaction with end-users, such as industry and manufacturing fields, organizations can "digitize" their operational

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processes to accomplish the experience of DT. For example, with improved engineering tools, they can increase efficiency, cost-effectiveness, and the quality of products or services [3]. However, due to a lack of systematic knowledge, most industry and manufacturing enterprises fail to combine industrial domain knowledge with DT, leading to the current DT phase-only state with the automation stage. That is to say, the degree of DT is still in a stage of relative infancy in the industry and manufacturing domain [10].

Digital technologies can be broadly recognized as encompassing wearable devices, the internet of things (IoT), cyber-physical systems (CPSs), big data analytics, smart-sensing networks, sensor technology, brain–machine interface, cloud computing, edge computing, mobile crowdsensing systems, immersive technologies, artificial intelligence (AI), ambient intelligence, AIoT (AI + IoT), etc. These technologies have been implemented as new instruments to play a fresh melody of industry development in recent years. Numerous DT studies have been primarily explored and discussed in manufacturing fields from an engineering perspective. The increasing complexity of the new paradigm shift driven by DT implies that prior attempts to advance theoretical or normative insights through a singular disciplinary lens are no longer significant. Recently, some studies have reviewed DT papers to obtain findings regarding the DT phenomenon, DT definition, DT success principles, and DT research topics [1,10]. For example, Vial [1] studied 282 research works of digital transformations and proposed an inductive DT conceptual model, including criteria of disruptions, strategic responses, use of digital technologies, changes in value-creation paths, organizational barriers, negative impacts, and positive impacts. The development of DT can improve production efficiency, reduce operating costs, and avoid human governance abuse. At the same time, it can predict more industry and manufacturing development trends for enterprises and capture future development opportunities [1,2,11]. This dynamic pace of DT development may also bring about new challenges related to its implementation across all industries [2,8]. One key challenge is the lack of a comprehensive understanding of the DT phenomenon and its in-depth insights into industries and critical factors for market success [1,7]. Another crucial aspect of DT involves the use of new and emerging technologies. These tools are typically applied to address demand-pull factors, like value-adding customers, or technology-push factors, like improving the manufacturing or engineering process [3,11,12]. Past reviews of advanced manufacturing and engineering fields did not have the knowledge of DT in the literature corpus. Thus, state-of-the-art, popular research topics, research questions, and future directions about DT in the advanced manufacturing and engineering fields are still ambiguous and need to be revealed. Hence, this study reports on a survey of the literature on DT studies in advanced manufacturing and engineering.

This paper aims to reflect on the literature from mainly the "engineering" and "manufacturing" fields to understand DT and stimulate future research by providing strategic imperatives and presenting a research agenda. We have the following two objectives: first, understand and depict the association of research articles for DT; and second, present a research agenda that guides future disciplinary research on the DT of advanced manufacturing and engineering.

The organization of this study is as follows. The methods of collecting related literature are presented in Section 2. Results of informetric networks and results of topic modeling using a machine learning (ML) method titled Latent Dirichlet Allocation (LDA) are revealed in Section 3. Section 4 gives an in-depth review of the research topic. Section 5 summarizes the research topic, research questions, and future research agenda, and Section 6 concludes this study.

2. Review methodology

We used documents indexed in the Web of Science (WoS) database. This database offers comprehensive coverage of scientific publications from more than 3,300 selected publishers and 12,000 high-impact journals, as well as a five-reference index with more than 1 billion cited references [13]. The index reflects Garfield's law of document sets and Bradford's discrete law, subject to strict procedures and high standards [14–16]. In addition, WoS supports data curation for each cited reference in any bibliographic record, making it valuable for both bibliometric analysis and topic modeling. We undertook a systematic review of the literature in the most comprehensive scientific database WoS to answer the following research question: How has DT contributed to the development of advanced manufacturing and engineering? We adopted a three-phase methodologic approach (Fig. 1) based on the study steps of Yigitcanlar et al. [17].

To establish a foundation of DT in advanced manufacturing and engineering, we applied two complementary sets of analytical algorithms: 1) bibliometric analysis and 2) topic modeling [13,15,18]. According to a quantitative assessment, the bibliometric analyses focus on co-author, co-word, and co-citation clusters. The analyses objectively depict the current status of studies [14]. Such analyses establish a comprehensive view and evaluation of DT studies in advanced manufacturing and engineering [15,19,20].

For topic modeling, we used LDA, which reveals co-occurrences among words and long-span latent topic information. The modeling method investigates topics that receive the most research attention, identifies underlying topical trends, and finds the most relevant documents for each topic [18,21]. In the following subsections, we provide details of the data collection, followed by information on the analytical algorithms and procedures.

2.1. Article collection and corpus creation

The literature source included the WoS database from 2000 to 2020. We conducted the query in August 2020. Considering the fields of interest, two stages were conducted to identify target papers. In the first stage, "Selection of keywords," we defined six sets of topics keywords:

a. "Digital transformation" and "engineering."
b. "Digital transformation" and "manufacturing."
c. "Digital transformation" and "civil."
d. "Digital transformation" and "construction."
e. "Digital transformation" and "transportation."
f. "Digital transformation" and "logistics."

Over 1,118 research articles were found to match with the selected keywords (see Fig. 1). In the second stage, "Identification and screening," duplicated papers were removed using these six sets of keywords, which were combined using the Boolean operator 'OR.' In total, we screened the articles down to 832 pieces. From this list of papers, we derived our preliminary set by including articles from journals and patent documents. We removed all conference papers, patents, and relevant articles which were not journal papers in this step. This resulted in a set of 273 articles. To identify the most closely related literature, Scientific Citation Index (SCI) Q1 high-impact journal papers were selected from the 273 articles, and the results were narrowed down to 99 pieces. Finally, these 99 articles were reviewed, categorized, and analyzed.

2.2. Corpus visualization by informetric networks

Publications descriptive statistics were gathered and analyzed. Published documents on DT from 2000 to 2020 were analyzed according to their year of publication, topic related to advanced manufacturing and engineering, countries or regions.

We then conducted keyword analysis, in which each keyword that appears in the topics of each paper is visualized as a node. If an article has two keywords, this paper has two nodes. If both nodes appear in the same document, they form a co-occurrence. If these keywords appear in multiple publications, the co-occurrence is strong. The higher the co-

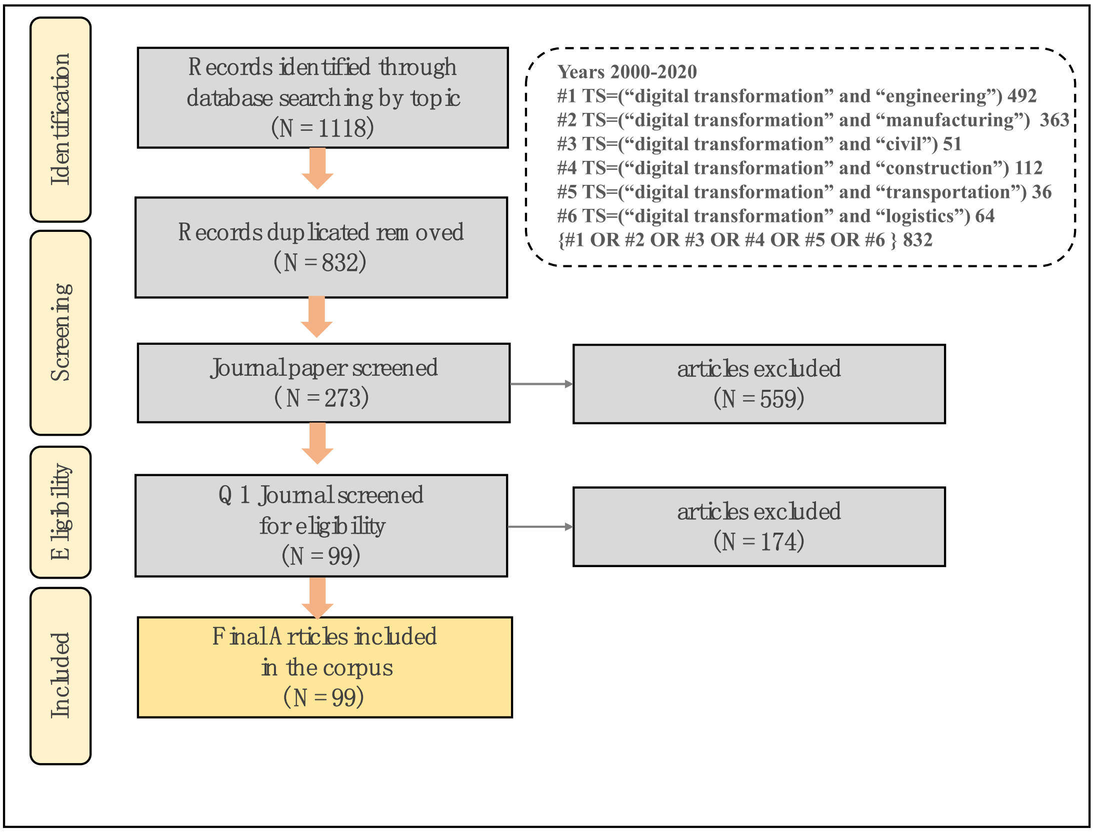

Fig. 1. Procedure of article collection and corpus creation.

occurrence, the more critical these terms are in this field. Based on the concepts above, co-word density analysis and co-word network analysis were visualized using the network-visualization tool VOSviewer to convert all the keywords into a co-word matrix. This is a two-dimensional data matrix used to record the co-occurrences of all keywords. Then, we also used the co-word matrix to develop a co-citing source journals cluster. The bibliometric visualization figures are depicted in the next section.

2.3. Topic extraction and clustering by machine learning

Topic modeling is a text-mining technique often used in ML and natural language processing. Given a collection of documents, it provides a way to discover the hidden topics within papers. Each topic is presented with a collection of words that make sense together. These topic-associated words can help organize and offer instructive data structures to understand large collections of unstructured text bodies. Several topic modeling methods have been devised over the decades, and LDA [22] is one of the most popular and well-studied methods. Thus, LDA was adopted in this review study to analyze the collected papers. Notably, LDA uses the "bag of words" concept in the model without considering the sequence and the grammar in the document; however, it can identify the data collection's topics or structure without human intervention.

In the literature review, it is reasonable to assume that the collected documents for a specific problem cover a homogenous list of topics. A review paper normally aims to review recent progress and provides a compact summary of the collected research papers on a particular topic, so it is reasonable to use LDA to perform an initial analysis of a review paper. This can explain why many review papers have used LDA to discover the topics underlying the collected documents and obtain insights from the inference results. For example, Antons and Breidbach [23] reviewed service science research using LDA. Annie et al. [24] integrated LDA, K-means (Clustering), and normalized term frequency-inverse document frequency (NTF-IDF) approaches to discover the significant trends in deep learning for computer visions.

LDA is a three-level hierarchical Bayesian model in which each document comprises a finite mixture of topics, each of which is featured by a distribution over words. LDA's inference requires computing the posterior distribution of the latent variables given the observed words; however, the posterior distribution is intractable for exact inference [22]. Several approximate inference algorithms have been introduced to estimate model parameters, and the most dominating inference techniques are variational inference and Gibbs sampling. Both approaches have advantages and disadvantages; this review used an online variational Bayes algorithm [23].

We attempted to find the topics from the 99 articles on DT in advanced manufacturing and engineering. Subsequently, we visualized the topics with their associated top-20 words to help readers interpret and understand the research topics within the collected papers. In our corpus of DT articles, all review papers used a manual-coding approach to classify documents, so the method used in this study is novel in reviewing DT literature.

3. Results of informetric networks

3.1. Distribution of publications

This review used the time interval from 2000 to 2020 as the criterion to select papers for the subsequent review since the popular adoption of the Internet is an important component in DT, and the rapid growth of the Internet can be dated back to 2000. Published data from 2000 to 2020 regarding DT in advanced engineering were gathered from the WoS database (Fig. 1). Industry 4.0 is the era of using information technology to promote industrial transformation, and it is closely related to DT. The term "Industry 4.0" was first introduced in 2010 at the

Hannover Fair in Germany. Its appearance became the fashion of the day in the DT research field. After this, we can see a research mainstream beginning to focus on DT. Fig. 2(a) shows the published documents on DT from 2000 to 2020. From 2016 to 2020, the number of articles increased sharply, from around 4 to 45. Fig. 2(b) shows the top sources publishing works related to advance manufacturing and engineering. The top five serials are *Sustainability* (16), *IEEE Access* (6), *Production Planning & Control* (6), *Technological Forecasting and Social Change* (5), and *Automation in Construction* (4), *Computers in Industry* (4), and *IEEE Software* (4). Fig. 2(c) lists countries or regions active in this field, of which Germany, Spain, Switzerland, China, and the United Kingdom are the top five.

3.2. Data visualization of publications

3.2.1. Keyword density analysis

Keywords density visualization presents the co-occurrence of keywords directly (Fig. 3). The more keywords around the node and the higher their frequency the deeper the color appears (shown in red in Fig. 3). It can be seen from the map that the top five keywords with high frequency in DT research are *digital transformation* (33 times), *Industry 4.0* (31 times), *big data* (16 times), *future* (15 times) and *innovation* (14 times). *Digital transformation* is usually linked to *Industry 4.0*. The digital-enabling technologies including *big data*, are driving fundamental market shifts and a new wave of digital-driven disruption accelerating the industrial revolution. The term *Industry 4.0* is *future-oriented* and refers to the significant innovation taking place in the way goods are produced and delivered. These keywords show the hotspots in the research field and with those keywords at the center each spread to some related hot academic issues.

3.2.2. Keyword network analysis

VOSviewer was used to construct maps of keywords based on co-occurrence data (Fig. 4). We set the minimum threshold of keyword frequency as four. Results showed 43 keywords, leading to four clusters with 453 links. Node labels represent keywords. The larger the node, the more significant the proportion of the keyword is. The distance between nodes indicates the strength of ties between them.

Cluster 1 is marked in red and contains the keywords Industry 4.0, big data, ML, etc. Cluster 1 focuses on exploring essential technologies for DT against the background of Industry 4.0. Cluster 2, marked in green, contains DT, design, smart, digitization, strategy, collaboration, and performance, focusing on development trends and DT orientation. Cluster 3 is marked in blue and contains nine keywords, including innovation, opportunities, challenges, etc., focusing on the realistic background and approaches to realize DT. Cluster 4 is marked in yellow and contains nine keywords, including smart manufacturing, industries, supply chain management, etc. It focuses on the application scenarios of DT.

3.2.3. Bibliographic coupling network visualization

We analyzed the bibliographic coupling of citation references and constructed the network visualization (Fig. 5). The results show that *Technology Forecasting and Social Change* has the highest total link strength. The journal has established the most robust bibliographic coupling relationship with the other 11 journals. Among the 12 journals, *Technology Forecasting and Social Change*, *Production Planning & Control, Sustainability, International Journal of Production Economics* and *Journal of Cleaner Production* have strong connections with each other. Papers in these journals are related because they may cite the same papers.

For example, "Industry 4.0," published in *Business & Information Systems Engineering* by Lasi et al. [25], has 12 citations. "Industry 4.0: State of the art and future trends," published in the *International Journal of Production Research* by Xu et al. [26], has eight citations. "Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0," published in *Technological Forecasting and Social Change* by Muller et al. [27], has eight citations. Further, it can be seen from the map that journals are classified into three clusters and marked in different colors. Journals in the same cluster are closely related to their research direction and are very much in line with each other.

3.2.4. Co-citation of cited references network visualization

We also analyzed the co-citation of selected references, setting 20 as the minimum citation threshold (Fig. 6). Among the same 2,879 references, 42 references met this requirement and were included in the analysis. Four clusters were obtained from the 42 cited references, each of which was expressed in a different color. The 42 label nodes represent 42 journals. The size of the node represents the proportion of the number of citations in a journal. The connection between two points means two selected papers have a co-citation. Meanwhile, the length of the link represents the correlation between the two journals. The shorter the connection distance, the stronger their correlation is.

4. LDA topic modeling and discovery

Following the rigorous preliminary screening process as outlined in Fig. 1, the large number of relevant publications was consolidated to 99 articles. This number presented a reasonable amount of publications that the research team could read and analyze in significant detail.

Each paper normally comprises several topics, and the words in the papers should be coherent with the topics that the users would like to present. Thus, applying LDA to identify topics and their associated words helped us perform the initial analysis. LDA comprises a hyper-parameter that is about the number of topics in the corpus. Three approaches for determining the most suitable number of topics—that is, perplexity scores, coherence scores, and topic-modeling visualizations—were deployed in this research. The perplexity score is the most conventional metric in language modeling, with a lower perplexity score indicating better generalization performance. Notably, the perplexity score is the metric used by Blei et al. in key LDA papers [22,23]. During DT collective papers' topic modeling, the better perplexity scores are found when the number of topics is 5, 6, or 7 (Fig. 7). The second approach involves using the coherence scores to assess the quality of the discovered topics. The coherence scores for all possible numbers of topics are in the range of 0.48 to 0.49, showing minor differences in performance. Finally, we visualized the topic modeling results, as shown in Fig. 8 (where the number of topics is set as 6). Integrating the three topic-modeling measurements, the setting of six topics for LDA modeling was applied for the subsequent analysis.

The topic-modeling analysis reveals six dominant domains and their associated words, as shown in Table 1. We also considered the connectedness, correspondence, and relative significance of these topics in this section. The visualization result for the six groups is listed in Fig. 8.

4.1. Topic 1: Smart factory

We labeled topic 1 "*smart factory.*" The smart factory category mainly discusses the advantages and application prospects of the smart factory approach. The contents can be summarized as follows:

(a) The rising background of smart factories and their advantages compared with the traditional factories are explored.
(b) Exemplars of the enabling technologies and high-tech equipment and how they are applied in the smart factory are provided.
(c) Solutions for the technical bottleneck of the smart factory applications are proposed.

The smart factory concept is envisioned as a factory that mainly operates without a human workforce and enables the achievement of mass-customization of products [28,29]. The smart factory can benefit from advanced digital tools to reduce costs, increase productivity, and

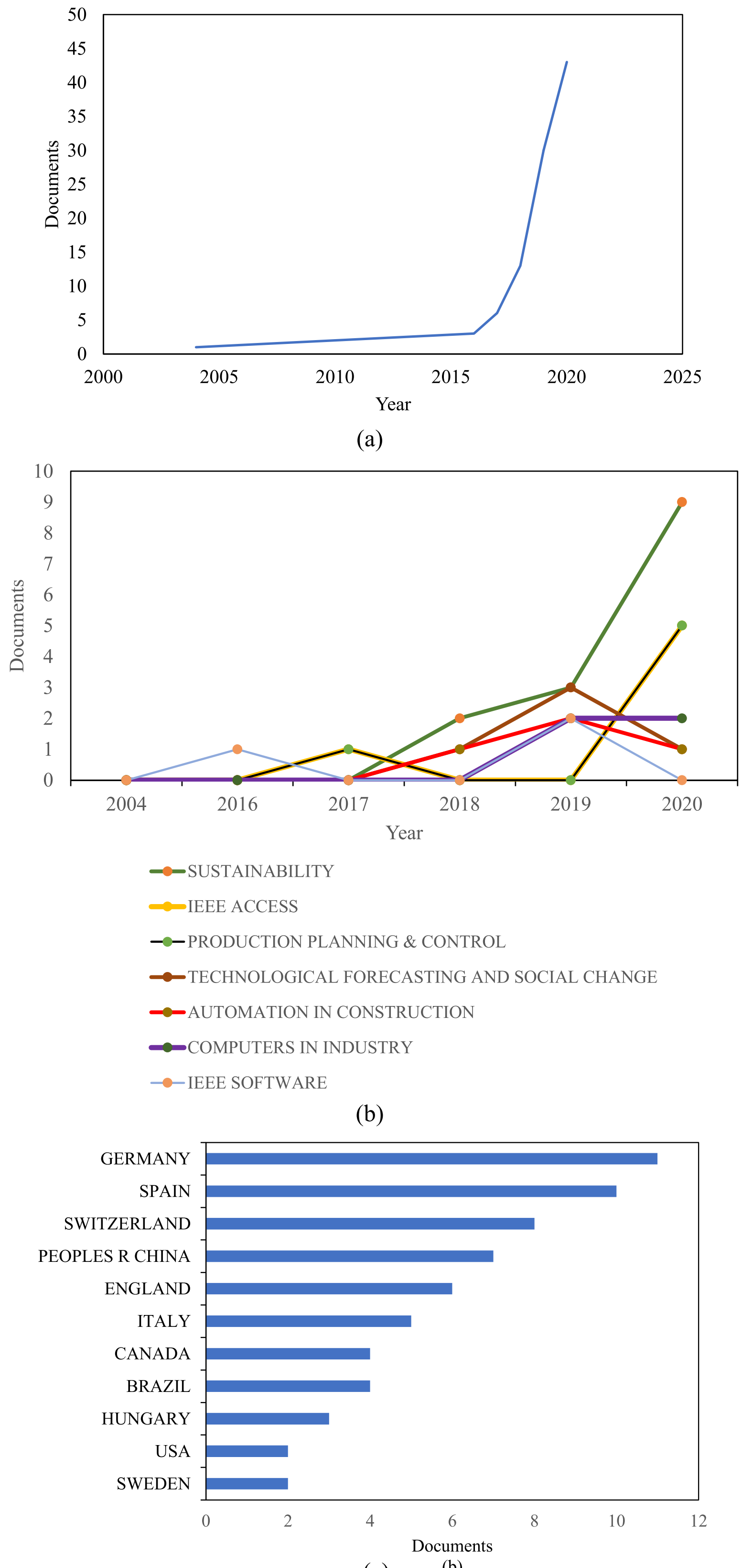

Fig. 2. Statistics from the WoS database (August 28, 2020): (a) published documents per year; (b) published documents by source; (c) published documents by country/region.

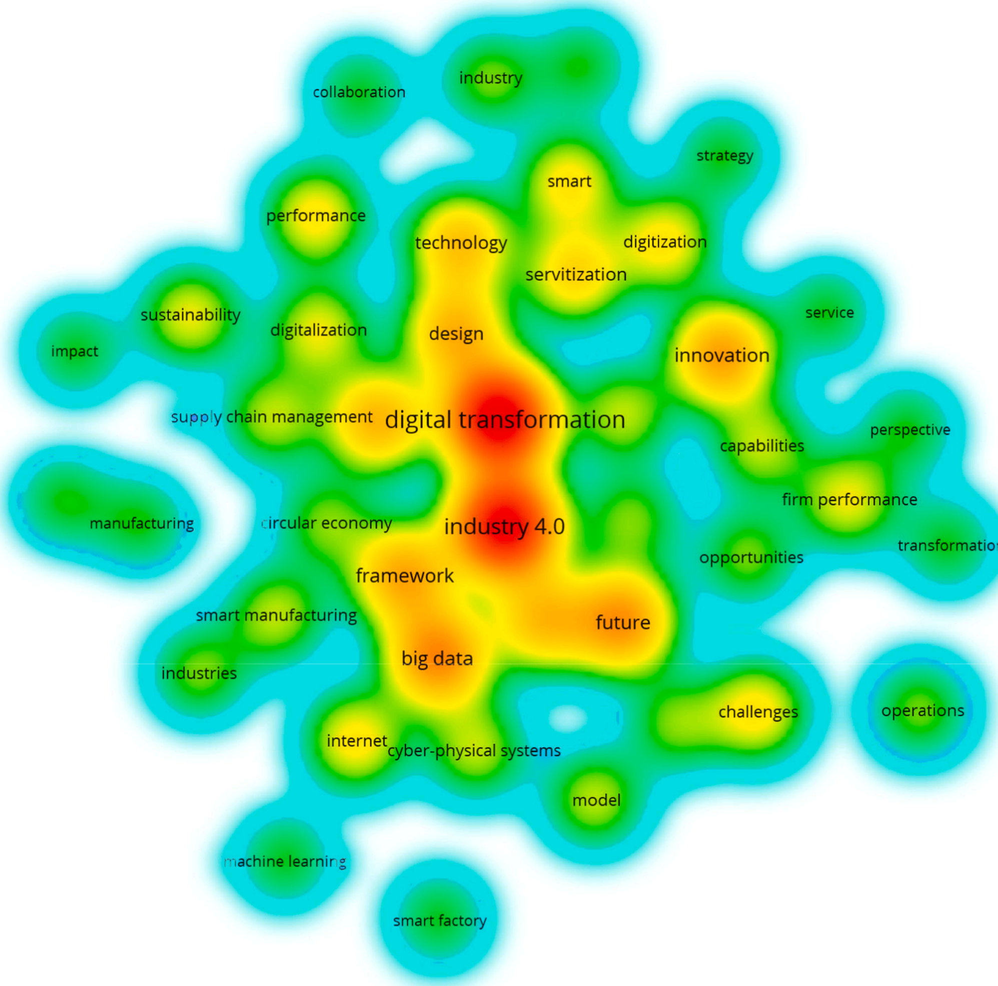

Fig. 3. Keyword density visualization.

enhance customer focus across various value chain elements [30]. In the past, process planning depended on the engineer's experience and domain knowledge of the production facilities, processes, and equipment, making it a time-consuming task in the factory.

The smart factory can meet the needs of individual customers and profit from small-unit production. How a company responds in the new environment and how its resources are to be distributed to optimize production and product transactions within their capability are serious issues. To address this paradigm, several new models appeared. For example, a high level of work automation, the adoption of predictive analytics, and advanced computer-aided process-planning systems enable the process plan to be generated based on the results of applying big data analytics to the data collected from machines, tools, and associated databases [31].

The realization of the smart factory relies on smart machines, meaning that the machines in the smart factory should be equipped with sensors and actors so that they can communicate with each other to adapt their processes [31].

The sensor data must be collected and transferred to the cloud for further processing using big data analytics. Subsequently, the analyzed results are sent back to the machines to enable re-parameterization of machines, predictive maintenance, and process optimization. Optimal re-parameterization in CPS is one of the bottlenecks during the DT of the manufacturing industry. Villalonga et al. [32] proposed a cloud-based method comprising learning and the optimization of computational procedures to deal with this problem. Although smart factories have been considered as the future of manufacturing, the infrastructure for many traditional industries is not ready for the adoption of smart factories, so Industry 3.5 was proposed as a hybrid strategy by upgrading existing systems with big data analysis and decision-making processes of industry [33,34].

4.2. Topic 2: Sustainability and product-service system

We labeled topic 2 "*sustainability and product-service system*." The *sustainability and product-service system* category mainly discusses the sustainable development of DT and the various sustainable functions required for an organization's transformation. The contents can be summarized as exploring: (a) the integration of DT and sustainable development, (b) the various sustainable functions designed for DT and the complex relationships between them, and (c) how to reduce the resistance to DT and maintain the sustainability of employees' careers.

DT determines the sustainable development of the organization in the future. The transformation process requires the integration of digitalization and sustainability. To achieve sustained success, organizations need to conduct sustainable DT from a longer-term and dynamic improving perspective [34–38].

The circular economy business model driven by DT is the right combination of digitalization and sustainable development [39]. To a large extent, the digital economy can effectively eliminate the excessive consumption of resources and energy in traditional industrial production, thereby achieving sustainable development [36]. The digital

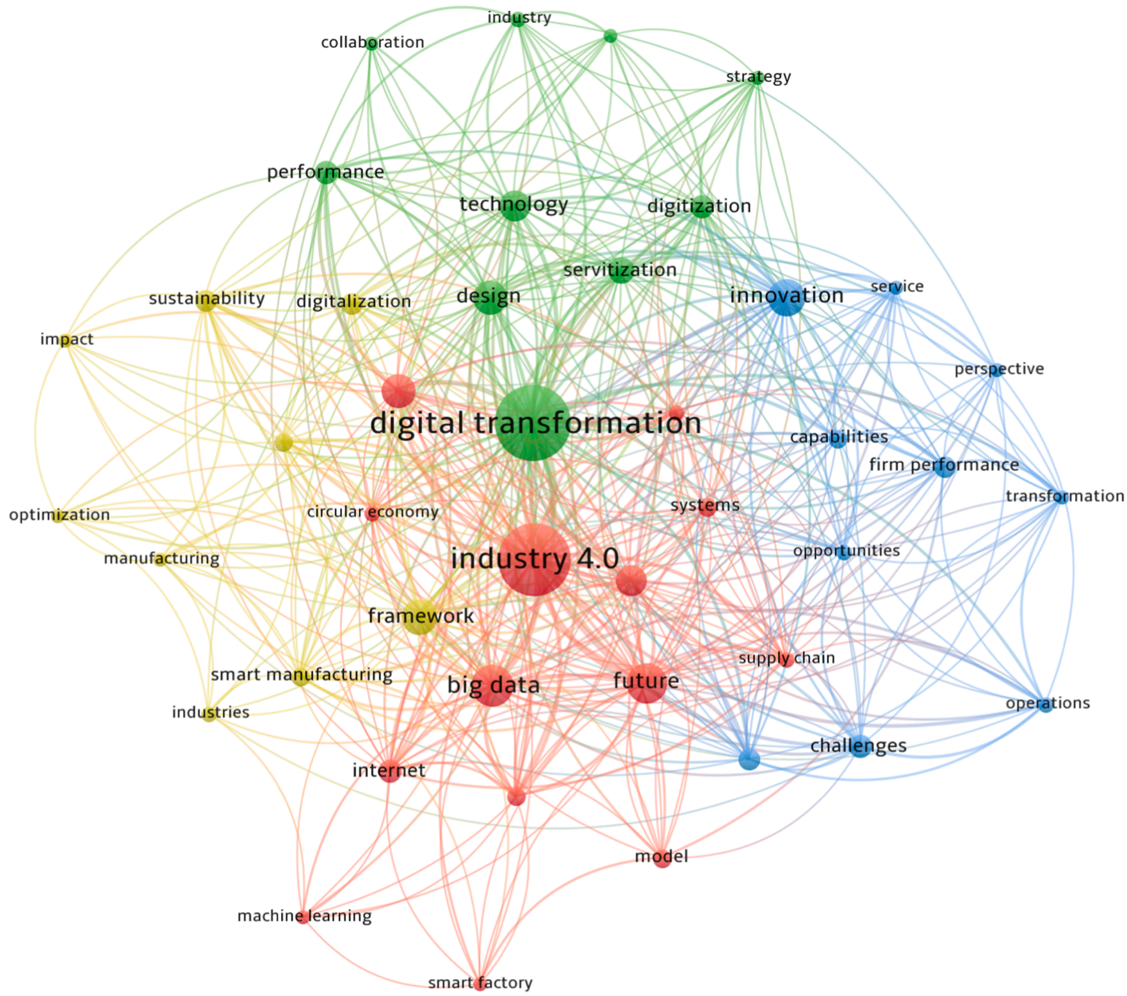

Fig. 4. Keyword network visualization.

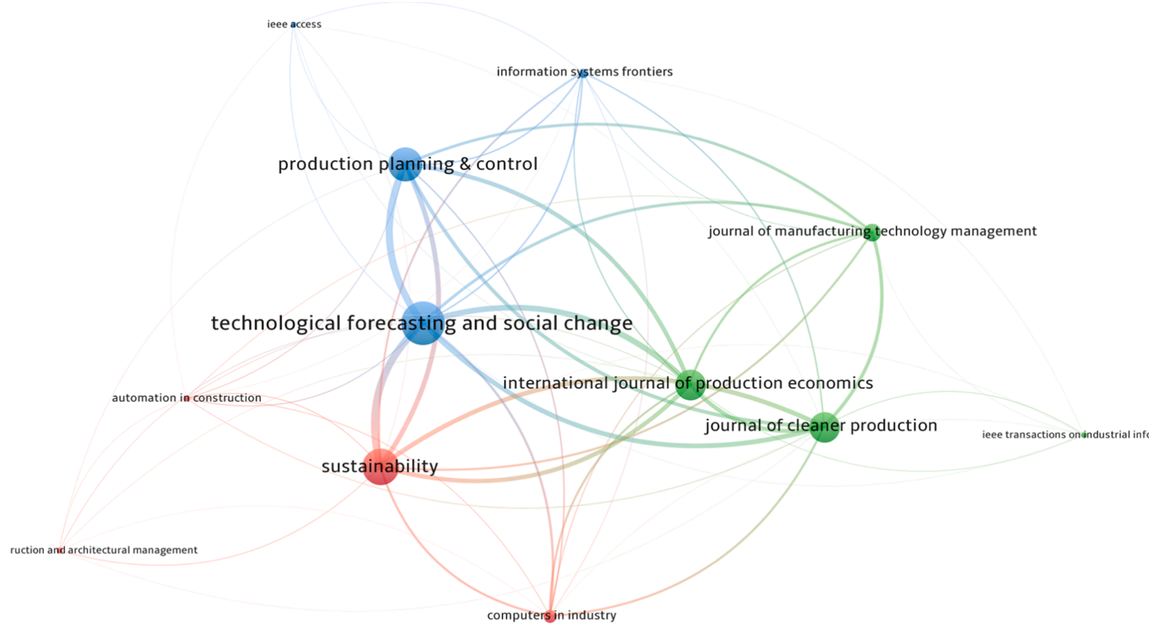

Fig. 5. Bibliographic coupling network visualization.

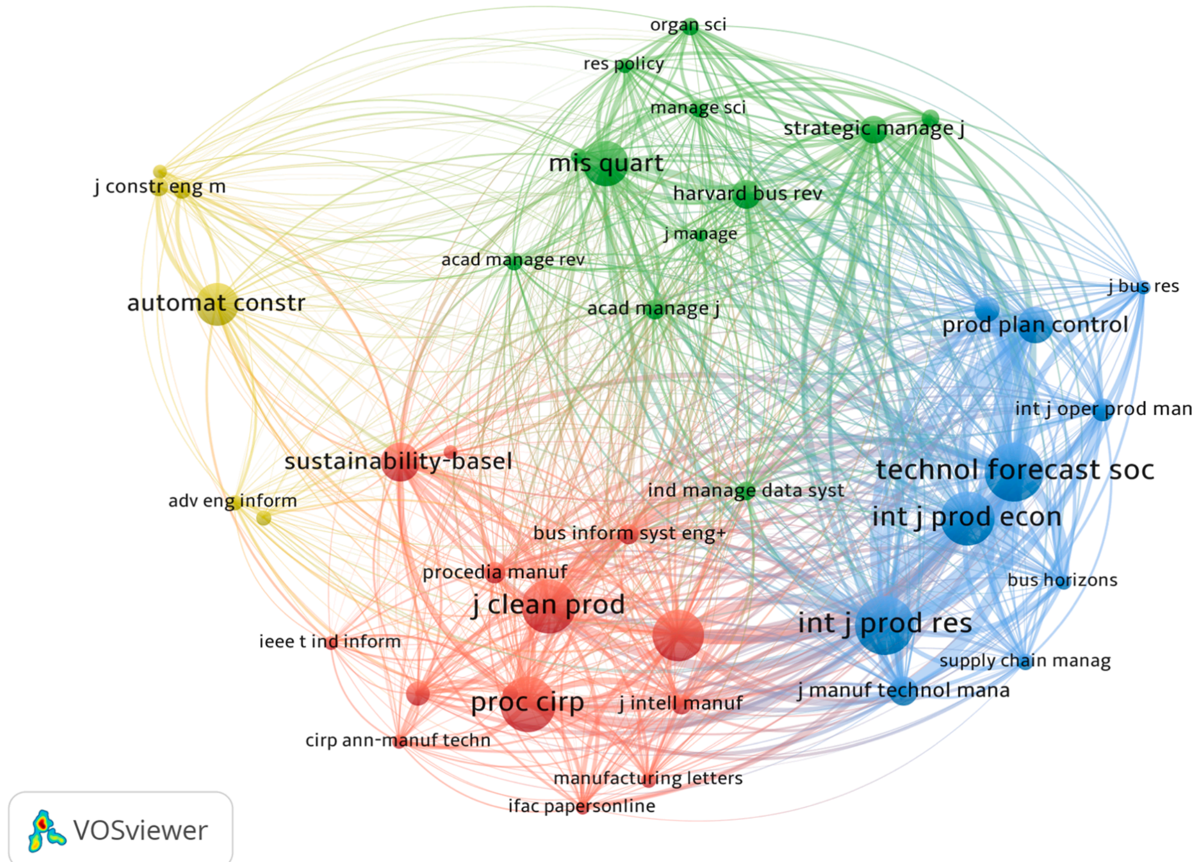

Fig. 6. Co-citing source journals cluster visualization.

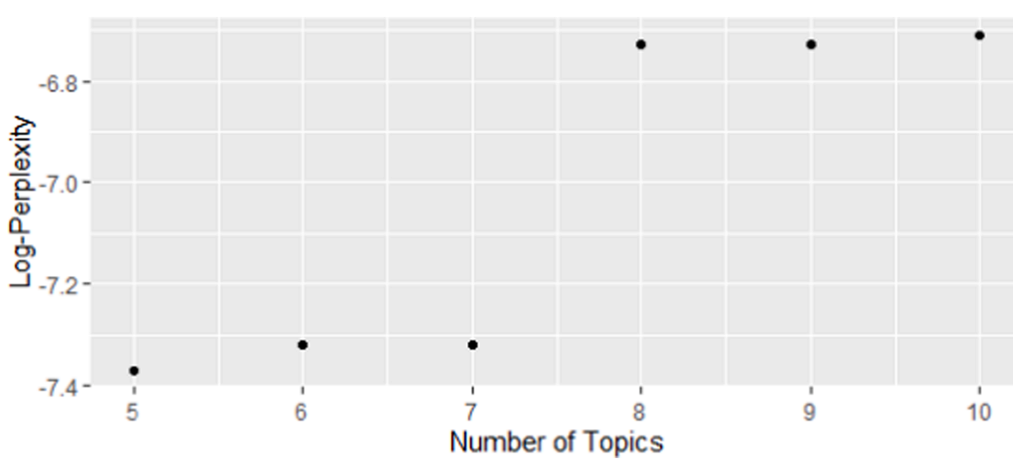

Fig. 7. Log-perplexity scores for different numbers of topics.

construction of a circular economy requires the creation of an information network and database platform. Thus, enterprises can carry out an efficient production process to achieve the goal of a circular economy.

The concept of sustainable development and its function in DT can be considered from the three aspects of society, environment, and economy. Sustainability is not the DT component, but it brings expanded functions of transformation, such as improving personnel health, operational safety, waste management, energy consumption, and environmental impact. With the advancement of industries' or organizations' DT, different sustainability functions will be produced accordingly [34,40].

In addition to environmental protection, sustainability is also related to the protection of economic and social resources. There are also complex logical relationships among the various types of sustainability-related functions of DT. Economic sustainability functions (such as production efficiency and business model innovation) are often a direct result of DT, paving the way for social, environmental sustainability functions (such as reducing energy consumption and harmful emissions) and sustainable social functions (improving the living environment) of DT [40]. Especially in the manufacturing industry, industrial DT will reduce waste emissions in the manufacturing process, improve the efficiency of energy and material utilization, and reduce economic costs. For example, digital technologies such as digital twins, three-financial, benefit, effort.

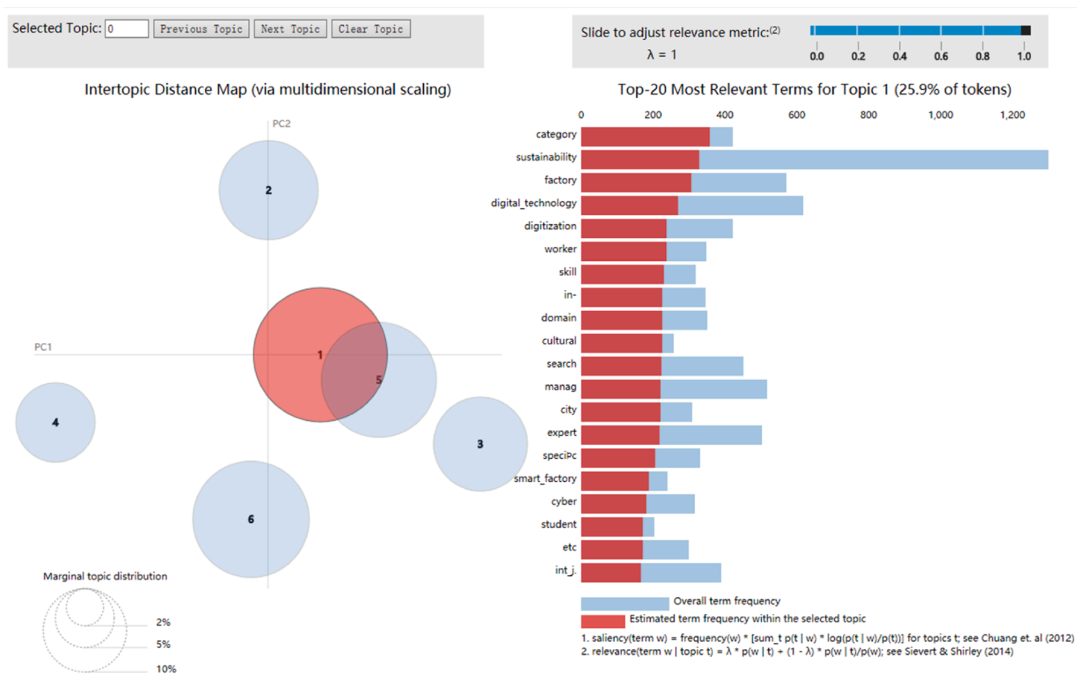

Fig. 8. Illustration of topic-modeling results and the most representative phrases of topic 1.

Table 1
Dominant topics in research on DT for advanced manufacturing and engineering.

Topic Number	Label of the topic	Words of LDA topic discovery
1	Smart factory (9 articles)	Sustainability, factory, digital technology, digitization, worker, skill, domain, management.
2	Sustainability and product-service system (10 articles)	Sustainability, circular economy, environmental, servitization, value chain, product service, digital twin.
3	Construction digital transformation (8 articles)	Building Information Modeling, construction, 3D printing, additive manufacturing, cluster.
4	Public infrastructure-centric digital transformation (8 articles)	Air, maturity, route, sustainability, public, contract, readiness, employee, procurement.
5	Techno-centric digital transformation (36 articles)	Blockchain, schedule, algorithm, IoT, ML, security, mobile, appliance, vehicle, route, edge.
6	Business model-centric digital transformation (28 articles)	Firm, digitalization, culture, employee, digital technology, portal, SMEs (small and medium-sized enterprises), lean, partner, barrier, leadership, expert, financial, benefit, effort.

dimensional (3D) modeling for design and manufacturing, and 3D printing have advantages in optimizing resources, reducing material consumption, and accelerating production processes [2].

Digitization and automation enhanced by DT, such as the implementation of digital twins, significantly reduce the workforce and manual efforts in production processes [41]. Once employees realize that DT may threaten their jobs, they may resist DT changes. Thus, companies should deploy and apply digital technologies emphasizing employee empowerment in computer-assisted DT implementations [41]. Providing employees opportunities to improve their professional skills and real-time manufacturing knowledge for product-service systems are the key foci in topic-2-related literature [42,43].

Further, recent review papers on the technology development of digital twins across the aspects of product designs and intelligent manufacturing (Industry 4.0) are complementary and critical to this topic; however, due to page limitations, these are not elaborated further in this paper [44,45].

4.3. Topic 3: Construction digital transformation

Judging from the top 20 most representative phrases for topic 3, topic 3 is labeled *construction digital transformation*. Papers categorized under the *construction digital transformation* label are those that provide insights into "what are the driving and influencing factors of DT in the construction industry and the empirical applications and scenarios of diverse DT technologies applied in the construction industry?" Research in this area can be summarized as: (a) discussion of the dilemma and uncertainty of DT in the construction industry; (b) studies of the functional, scenario-oriented, data-oriented DT in the construction industry and the implementation path; and (c) exploring the DT evolutions and transformations from the Construction 3.0 to Construction 4.0 era (Industry 4.0 in the construction industry).

The acceptance and implementation of advanced digital technologies in the construction industry are, on average, lower than other high-tech industries [46,47]. However, the advent of the Industry 4.0 trend has brought disruptive transformations to the construction industry [46]. Some inherent characteristics of the construction industry are still obstacles on the road to effective DT. The profitability of the construction industry is relatively low, and the huge investment in DT is a serious consideration [47,48]. Meanwhile, on average, lower-educated on-site workers and lower profit rates in the construction industry are also obstacles to using advanced digital technologies to implement DT [47]. Organizational resistance to DT exists due to the misunderstanding of digitization as a kind of "redefining and subverting the industry" label [49]. Thus, low readiness for digitalization and low maturity of DT are present in this industry.

By making better use of advanced digital technology, the realization of construction projects' planning, design, resource allocation, construction, final construction delivery, subsequent maintenance, upgrading, and reconstruction can be transformed as a new DT-based life cycle and value chain, with digitalization, automation, and intelligent management and control [47,48]. For example, establishing the decision support system based on Building Information Modeling (BIM) for design can achieve better on-site decision-making. Using digital twin technology can also create a virtual copy of the building body to conduct real-time simulations and predictions [49]. Moreover, developing solutions based on distributed ledger technology and additive manufacturing (AM) technology can effectively build highly complicated buildings and reduce on-site labor costs and improve building quality [47,50].

Research has mainly explored the enhancement of BIM, digital twins, and AM technology in the construction industry [47,50–52]. BIM has played a fundamental role in the digital transformation of the construction industry. BIM is a digital system used in engineering design and construction management. It is used to generate, manage, and share building information among project participants. BIM is usually combined with other digital construction technologies and applied to construction projects throughout their life cycle.

BIM can model the 3D spatial data of the site and the proposed building, determine the spatial orientation and appearance of the building, and establish a connection between the building and the surrounding environment [51,53]. During the construction phase, BIM can provide accurate engineering quantity statistics. This facilitates cost estimation, engineering budget, and final accounts. In addition, by linking with the construction schedule, spatial information and time information can be integrated into a visual 4D (3D + Time) model so that BIM can organically integrate building spatial information and equipment parameter information. In this way, managers, designers, and engineers can obtain overall building information and complete building information data provided by BIM during project delivery and acceptance, as well as subsequent building maintenance and asset management phases [51,53].

Digital twin technology is the digital expression of physical products in a mapped virtual space, making it easy for us to see what might happen to the actual physical product on the digital system. It replaces physical resources with digital information to reduce resource waste and production costs. In the process of building construction, it is necessary to ensure the timeliness of warehouse scheduling and material replenishment, and building material suppliers are required to make real-time and dynamic decisions. Assembling sensors in the warehouse makes it possible to create a digital twin of the warehouse, collect informational data to support decision-making, and ensure the timely supply of building materials [46]. Therefore, digital twin technology is also the key digital technology of Architecture 4.0.

Another key enabling technology in Construction 4.0 is AM. AM is based on digital modeling files and is driven by 3D data to directly manufacture physical objects. AM is an agile manufacturing method in which materials are accumulated layer by layer. AM can carry out the modular design of the entire building, and print the building modules with a 3D printer, and, finally, transport them to the construction site for assembly. The AM process can flexibly change the architectural design, greatly reduce production time and cost, simplify the supply chain, and reduce inventory pressure [49].

4.4. *Topic 4: Public infrastructure-centric digital transformation*

Judging from the top 20 most representative phrases, topic 4 is identified as *public infrastructure-centric digital transformation*. The research focuses predominately on higher education, public transportation, public culture activities, and public communications on political issues. The literature related to DT research under this category mainly discusses the impact of DT on public social systems, the responsiveness of public systems to DT, and related research on DT maturity. The contents of the research literature are summarized as follows: (a) What are the effects of DT in different areas from a public social system perspective?; (b) How can the public social system better respond to DT to maximize the effectiveness of the change and upgrade? and (c) How can the degree of readiness or maturity for DT and the design of a foresighted and future DT model in specific scenarios be evaluated.

DT has led to a shift in human society's production methods, the reconstruction of production relations, and the restructuring of economic structures [54,55]. Digital technology is widely used in various industrial areas of integrated transportation. By enhancing the coverage of the perception network of important transportation nodes, such as crucial road sections and flight sections, the deep sharing and opening of transportation information resources are enabled. Meanwhile, the efficient and sustainable development of public transportation is also being developed at a fast speed.

Improving public sector business processes through information technology can bring the following systemic benefits to public institutions. For example, timely information announcements of public transportation agencies, electronic public procurement, and digital announcement platforms can simplify the procurement process and realize the openness and transparency of the process. In addition, electronic public procurement can attract more digital companies to participate in the construction of smart cities and help create a new market outlook for new transportation services and other public services [56]. For example, in the digital transformation of public energy management, the digital energy storage technology can transform the energy storage system (ESS) into digital assets, completely changing the operation and maintenance of the traditional ESS and helping local public utility companies provide new network energy storage services and business models [49]. DT enables service providers to have a significant socio-economic impact on the entire society by improving resource utilization.

The culture-domain-based digitalization is closely related to citizen well-being. DT in the field of cultural consumption can improve the accessibility and openness of public cultural services, thereby enhancing citizen well-being. In other words, DT in the cultural field can bring more positive impacts by diverse and smart cultural systems (hereafter "smart culture") for individuals, industries, and society. As for individuals, smart culture can bring better personalized cultural experiences and reduce the time, economic cost, and distance barriers in the consumption journey. From an industry perspective, smart culture can help protect and promote cultural heritage and enhance industrial competitiveness. From a social perspective, smart culture provides new business opportunities and enhances economic drivers of cultural consumption [57].

DT has also profoundly impacted public affairs communication such as politics, economy, social, and technology for future industry impacts under the new digital economy era. It lowers the barriers to entry for communicators and re-transforms the vertical information flow in public affairs communication into a horizontal network [49]. The focus of traditional media in the digital political communication ecology is gradually replaced by self-media such as blogs. How the managers of relevant departments make full use of information technology to manage more social forces under digital thinking influence has become the key to the modern innovation of social governance capabilities in the future.

Digital technology has brought newer products and services that can improve the efficiency and comfort of people's lives. However, DT has encountered many challenges in the process of implementation. It is necessary to respond to the changes in the private and public sectors. Research literature shows that the specific digital skills that employees have limit the implementation of DT. Therefore, university education may need to reflect the current teaching mindset and methods to grasp digital-age opportunities [58].

The implementation of DT requires a holistic and macro perspective of the public sector, which focuses on hardware and software improvements in the production environment and includes new strategic directions and adjustments to business models [59]. The key to DT is integrating people, organizations, and technology to support emerging industrial applications. Organizations must be prepared for dramatic changes in the business environment and have practical and powerful tools to assess these digital concepts and technology implementations' maturity [60]. The evaluation of the digitalization degree of the industry through the digital maturity index system will help understand the factors that restrict a sector's transformation. In this way, we will be able to effectively obtain guidelines to perform DT, enabling organizations to identify the focus of future organizational changes based on a clear understanding of its situation [61].

4.5. Topic 5: Techno-centric digital transformation

We labeled topic 5 "*techno-centric digital transformation*." Papers categorized under this topic mainly focus on the usage, impact, and maturity of digital technologies in various industries. The contents in this field can be summarized as: (a) the application scenarios of digital technologies in various fields are exemplified; (b) the impetus of digital technology and socio-economic factors in accelerating the DT process is introduced; and (c) state-of-art digital technology and the breakthrough of specific digital technologies, such as CPS, the IoT, cloud services, and big data technology, are discussed.

One of the most widely used technologies over the last two decades is Internet technology, making many industrial companies integrate products and e-services into smart produce-service systems to deliver smart products [62–64] and satisfy individual customers' requirements [65,66]. Likewise, the marketing and tourism industries have to face the challenges of new digital technologies such as social media, mobile phones, and AI, and use these technologies to enhance customer experience or create new business models [67,68]. Even traditional industries such as architecture, engineering, construction [69], and chemical engineering [70] can benefit from AI and data science to extract useful insights to help make decisions.

Although digital technology is not the only factor that affects DT success—as other factors such as leadership and organization culture should be considered simultaneously—digital technology still plays an important role in enabling digitalization. For example, virtual product development can leverage 3D CAD to reduce product development time and cost [71], while 3D printing can enable visualization of fundamental theories in the class to help students learn new concepts [72].

CPSs are key components in Industry 4.0 by integrating sensor networks, intelligent computation, and control into physical entities. Frank et al. [73] conducted a survey in 92 manufacturing companies to understand the adoption patterns of Industry 4.0 technologies in these companies. The base technologies considered in their proposed framework comprise the IoT, cloud services, big data, and analytics.

Big data analytics can feed back the results to the machines to change machine parameters. This can result in a highly digitalized and connected environment where the machines and equipment can continuously improve processes through automation and self-optimization, giving a base to develop a smart factory [74,75]. Unlocking the mysteries of data to unveil valuable insights that spawn powerful business outcomes has become an important part of today's most successful companies [76].

Besides manufacturing, many industries can benefit from DT to grow and stay ahead of the competition. The software industry can use ML to develop an assessment tool for software release management [77], use text mining to help requirements engineering by analyzing user feedback to extract requirements [78] automatically, and use genetic algorithms to optimize the search process for the program transformation sequence [79]. Moreover, software verification and validation can be completed with automatic testing tools such as unit tests, functional tests, and usability tests [80]. Meanwhile, cloud-based software is prevailing worldwide; as such, developing container-based virtualization to yield better performance has become an important topic [81].

In supply chain and logistics, effectively sharing information regarding demand changes and inventory levels can improve the competitiveness of the company, and blockchain can provide a trustworthy way to enable supply chain optimization [82]. Healthcare and medical industries have used AI techniques to analyze large amounts of data to develop predictive models, discover patterns, and inform better decision-making for prednisone medicine and the Healthcare Industry 4.0 [82–86].

System vulnerabilities or security vulnerabilities are likely to be produced from each component technology as well as interworking. As interworking between connected software and devices increases, the attack surface is under a higher attacked risk [74]. All relevant parties can access these cloud data, with new security and privacy issues arising, such as security, confidentiality, data integrity, identity verification, access control, etc. [68,87]. Thus, from a technology aspect, a risk-diagnosis approach, intensive cryptography, effective data governance structures, software verification and validation technologies, and system vulnerability-discovering tools are effective security assurance methods [68,80,87]. Moreover, from a management aspect, different stakeholders have the right to upload data to the cloud. Companies need to strictly restrict data access rights and develop effective data governance structures to minimize the challenges in monitoring and collecting private customer data, aiming to improve data quality and use information governance to meet these challenges [68,74,80,87].

4.6. Topic 6: Business model-centric digital transformation

We labeled topic 6 "*business model-centric digital transformation*." Papers in this topic provide insights into "how DT can contribute to and improve the core competitiveness and help organizations build a new business model to create a new value. [88–90]" Insights are in-depth, exploring the internal and external influencing factors of enterprise DT, the impact of DT on enterprises, and the improvement of organizational performance after transformation. Research in this area focuses predominately on the contributions of DT and can be summarized as a) the internal and external drivers of or barriers to DT, b) research on the nature of new business models after the digital transformation of enterprises or industries, and c) the evaluation and measurement of impacts and enhancements of the new business model generated by DT that can bring organizational performances.

Customers' voices are easily revealed. Thus, improving consumer experience has become a critical business issue, which means that the traditional resource-centric strategy is shifting to a user-centric strategy [88]. Enterprises that can listen to customers and give them new value to satisfy their requirements can reconstruct new business ecosystems.

The research papers also identify the influencing factors of drivers and barriers of DT. Human resources are one of the main factors affecting the digital transformation of enterprises. The increasing shortage of labor is the major driving force of DT [89–91]. Enterprises can use digital technology to allocate employees to tasks that generate higher added value and improve production efficiency. However, new requirements of human resources also pose new challenges for the implementation of DT. Enterprises need to put a lot of effort into educating or training employees to form a new culture, new processes, and new working scenarios with DT. Meanwhile, this may result in increased time and capital costs [89]. An enterprise's financial resources also affect the implementation of DT, with positive drivers from reducing the human resources cost, inventory cost, and operation cost. With the high implementation cost and invisible organization-changing risks, unpersuasive empirical evaluation of performance outputs based on financial inputs of DT systems development will be a key barrier to DT-based organizational change [92,93]. Another important driving factor is the need to increase the quick and accurate responses of DT technologies to satisfy customer requirements and to lead the market.

Fierce market competition and pressure from competitors drive companies to create value for customers. Companies can increase their market share and competitive advantage through DT based on digital technology [94,95]. By improving productivity and quality, companies also aim to quickly respond to the market and satisfy diverse and dynamic customer satisfaction. Driven by different driving factors, enterprises can create new DT-based business models to better reconstruct the organization from a new value proposition and effectively capture new opportunities in the new DT era [96].

The research literature divides DT into stages: digitization, digitalization, and DT. Digitization is the encoding of analog information into digital formats so that computers can store processes and transmit such information. Digitalization describes how to use digital technology to change existing business processes. DT is the further stage after digitalization, describing the successful upgrade and change that lead to a new business model. Companies aiming to carry out DT need their own digital assets and need to equip themselves with digital agility, digital networks, and big data analytics [95]. The above stages require corresponding digital resources, organizational structures, growth strategies, and performance indicators. Enterprises may generate new DT-based business models while moving forward into the DT phase and achieve a DT-based market competitiveness level.

DT-based business models bring new organizational cultures. Adopting new digital technologies is not the goal of DT, but bringing essential organizational transformation is [97,98]. Constructing and launching DT systems is not enough—being only one wing for bringing transformation; establishing an innovative and learning culture and new organizational mindset is the other [99,100]. The innovative and learning culture comes from a series of mutually influencing and reinforcing value-actions. The development of an innovative and learning culture does not mean abandoning conventional organizational culture [90]. It requires new interpretation and adjustment to ensure the company's flexible competitiveness, facing uncertainty with the right DT-based capabilities and strategies in the digital economy world [101].

The research literature revealed that the use of contemporary management tools [102–105] and methods—Six Sigma, total quality management (TQM), balanced scorecard, rapid prototyping, customer segmentation, strategic mission, and vision planning—is significantly and positively related to the successful implementation of DT [106]. These managerial methods or systems can nurture readiness and are indispensable for implementing enterprise DT. Integrating the above management methods, combined with DT technology, can effectively enable digital business models.

For example, establishing a digital twin platform can provide companies with a comprehensive cyber-physical information view of product design, manufacturing, supply chain, customer experience, and profitability. The digital twin-based platform can build a sustainable digital business model and generate economic, social, and environmental benefits [107]. Companies can use digital twin technology to innovate and develop sustainable digital business models from smart manufacturing, smart product-service systems, and product life-cycle platforms. The innovation of the business model comes from two perspectives: servitization and digitalization. Servitization, a demand-driven approach, mainly focuses on bringing added value to customers. However, digitalization carries out transformations from generating value in a technology-driven approach. Enterprises may innovate their DT business models by integrating these two approaches [73,108].

The impact of DT business models on enterprises involves four major aspects: 1) financial efficiencies, 2) production enhancements, 3) new customer experience creation, and 4) strategic market penetration [36,108–113]. For financial efficiencies, embedding advanced digital technology into services or products can enhance, optimize, and create a better customer experience, shorten production time, reduce manufacturing and operation costs, and achieve revenue and profit growth. For production enhancements, the DT business model requires enterprises to rethink the optimization of their business processes [114]. Using big data, cloud computing, the IoT and other suitable advanced digital technologies can enhance information sharing and decision-making between organizations, increase productivity, and increase manufacturing flexibility and agility [115]. Using digital technology, the new customer experience creation aspect can collect data about customer preferences and requirements. These data enable companies to improve the customer experience by providing customized products to give quick and correct customer responses and bring better customer experience satisfaction [112]. For the strategic market penetration aspect, the new DT business model can enable enterprises to obtain further information about customers, thereby effectively discovering new market segments that they have never realized in the past. It can also enable effective stakeholder collaboration and enable enterprises to react quickly to market changes and penetrate new markets by accelerating research and development (R&D) and launching new products and services [115].

5. Future directions

5.1. Smart factory

Many digital technologies are needed to make a factory smart, including the IoT, CPS, cloud computing, and big data analytics. Big data solutions are required for smart factories as the sensors embedded in the physical objects can generate large amounts of data, enabling the adoption of NoSQL and MapReduce techniques to achieve the goal of real-time queries and random access to data without time-consuming operations [116].

The adaption of these technologies involves connectivity and integration among activities and stakeholders at all levels. Notably, these technologies are highly interrelated, and the initial investment in software and hardware is extremely high [117,118]. In addition, the smart factory has to deal with various challenges faced by traditional industry. We summarize several possible research directions that are related to the smart factory concept as follows:

- The simulation model of the ML-based and cloud-based Industrial Cyber-Physical Systems (ICPS) is relevant to digital twins. We believe this is an important research topic that needs to be further studied and developed in a proof-of-service scenario for further empirical implications.
- Further research of the different interpretations of DT in both the factory and the smart product-service systems should be explored.
- The transformation of smart factories will cause changes at all levels of the supply chain. How DT affects the new market position, supply chain networks, operations, and productions could be further explored.
- A plurality of use cases for more digital applications, software systems, ICPS, smart product-service systems and AI-aided manufacturing systems in different fields should be investigated.
- The smart factory relies on an integrated network system to communicate and share information. The research issues regarding security implementation in smart factories should be further explored.

5.2. Sustainability and the product-service system

The second important topic concerns sustainability and the product-service system. Sustainable DT keeps with the frontier of technology, but companies need to integrate sustainable development into the organizational structure and organizational culture. Bringing sustainability into the new digital business model is a change and upgrading of organization mindset, culture, and technology.

Gaining a deeper understanding of the circular economy, environmental, servitization, value chain, product-service system and digital twin disciplines involves answering several critical questions. Future research directions are summarized below:

- Investigations into how to bring the right economic, environmental, and social sustainable value and take care of the inequality impacts on enterprise DT, industrial DT, and social DT would be of value.
- A DT-driven circular economy business model considering different levels, relationships, dynamism, and contextualization aspects can be further verified and explored in-depth.
- Further research on topics including mitigating resistance to change and sustaining careers by workers can be conducted.
- Research topics regarding how to make useful and incentive policies to carry out effective DT in industries can be further investigated.

5.3. Construction digital transformation

The third research area is construction digital transformation. The construction sector has a wide range of businesses, including housing construction, road construction, port construction, bridge construction, and industrial construction. The difficulties of diverse domains and scenarios need to be overcome. Future research directions are listed below:

- Topics concerning the design and development of BIM construction services driven by the IoT, big data, AM, 3D printing and blockchain could be further studied.
- The sustainability and diffusions of BIM patterns could be explored more deeply.
- Investigations could include how to use emerging technologies and other possible change dynamics to achieve continuous performance and carry out a future and in-context scenario.

5.4. Public infrastructure-centric digital transformation

The fourth important research topic concerns public infrastructure-centric DT. DT has been a driver in making the shift in human society's production methods, the reconstruction of production relations, and the restructuring of economic structures [54]. It has also enabled the redesign of public social systems in different fields [55]. We have given an in-depth insight into DT maturity, DT readiness, public transformation, innovation performance, and digital procurement. Further possible research directions are summarized below from related studies:

- Investigating how to assess digital readiness and ensure better robustness of the public ecosystem while launching digital transformations.
- Investigating how to capture and predict ambiguous and unpredictable public users' dynamic requirements for different public service domains and design acceptable user requirement-centric, performance-centric digital transformation scenarios.
- Investigating how to effectively build a necessary technological or managerial standard in new public or industrial digital transformation scenarios.
- Investigations can be conducted into how the DT maturity model can be adapted and improved in smart factories, smart operations, smart product-service systems, and data-driven service system perspectives in the future.
- Industry 4.0 infrastructure and big data maturity could be adopted to evaluate and compare DT readiness in different countries, cities, or organizations. The readiness information might be the next step to drill down to the corresponding in-depth competitive strategy on market penetration and city development positioning, and workforce impact responses could be conducted as future research.

5.5. Techno-centric digital transformation

Various technology tools provide the technical foundation for DT. For example, the IoT provides a means for the manufacturing industry to integrate sensors and communication technologies to track the status of every physical object, enabling manufacturing companies to create innovative systems that integrate products, services, and customer data [73]. Cloud-based resource planning [87] and resource virtualization [119] are vital for implementing cyber-physical production systems and industrial IoT.

Integrating these tools into existing systems will also bring new challenges to DT. For example, the adoption of the IoT is expected to result in a large volume of data over a wireless channel. This requires the use of enormous bandwidth available at the mmWave spectrum for real-time data transmission [120]. Cloud computing makes it possible for companies to get software that meets the requirements of multiple cloud providers without developing the software from scratch. This can dramatically reduce development costs and boost business growth [121] but can also increase the risk of data security. We summarize several possible research directions that are related to techno-centric DT as follows:

- A valuable research topic is devising models to integrate edge computing, fog computing, and cloud computing to address the bandwidth limitation and latency issues.
- The reconfiguration and optimal re-parameterization in CPS are bottlenecks for DT. Studies regarding these issues should be further explored.
- Despite a broad discussion of Industry 4.0, there is currently an evident lack of studies analyzing the current readiness and barriers for the broader uptake of smart technologies, especially from a practitioner's perspective.
- Integration of smart products with e-service to create a smart product-service system can enhance customer experience. The research issues regarding how to develop long-lasting relations with consumers should be investigated.

5.6. Business model-centric digital transformation

The sixth important research topic concerns business model-centric DT. Traditional business models that mainly rely on products and services to create revenues will be shifted to profit-creating by new product-as-a-service models, smart product-as-a-service models or public-services provider models. In the new digital era, business models are undergoing tremendous changes with the rapid development of DT technologies, organizations, industries, and societies transformed into a new era. Customers' voices and requirements are easily obtained and revealed. Consumer-centric ecosystems are thus becoming the mainstream. Information asymmetry is invisible, and the influence of consumers is rapidly growing higher and higher. Further research is needed to answer an array of related questions, as summarized below:

- How do firms design and implement a new operating business model, considering organizational and managerial processes to effectively drive the evaluable and feasible transformations and create the new value for short-term, middle-term and long-term competitiveness?
- What enablers, technologies, and capabilities are required to empower DT efforts in different sectors/domains?
- How could digital technologies and data help the firm resolve its problems and promote value in different digitalization efforts related to the different manufacturing/service provider value chains for the firm and its customers?
- How can firms effectively conceptualize new DT business models by utilizing new product-as-a-service, smart product-as-a-service, servitization or public service models in different sectors with in-context domain knowledge?

- What are effective methods or frameworks to evaluate the DT business model from as-is challenges to to-be opportunities? What are the suitable evaluation criteria or factors (except for financial and benefit perspectives), such as the upgrade and transformation of culture, strategy, organization, leadership, core competence, supply chain business processes, market share or market position?
- What are the new DT-based marketing and R&D strategies based on the digital platform-driven inputs that are obtained from multiple users' cocreation, crowd-sourcing, crowd-sentiment, and engagement?

5.7. Summary of research focus and potential project areas

The objectives of this paper are a) to depict DT from the research literature and b) to present a research agenda and guide for future research on DT in manufacturing and engineering. The analyses in Section 3 resulted in six topics being identified, which were elaborated in Section 4. Furthermore, based on our experience and research outcomes so far in DT, some research projects that are relevant to these six topics were proposed (sections 5.1–5.6). It is clear that DT is an important research agenda moving to the future; there is a lot to digest. Therefore, this sub-section assists readers in digesting the research outcomes in this paper with a summary table (Table 2).

6. Conclusions

This research uses bibliometric analysis incorporated with topic modeling to investigate the impact of the three prevalent phenomena of our time—DT, engineering, and manufacturing—using a novel, systematic, and comprehensive review. In this paper, we attempted to generate insights to obtain an in-depth understanding of how DT can contribute to real performance and transformations in different engineering and manufacturing domains by undertaking a systematic review of the literature. Thus, we conducted a systematic review of DT in advanced manufacturing and engineering studies from 2000 to 2020. Related studies were automatically clustered using the LDA method and divided into the six aforementioned topics: *smart factory, sustainability and product-service system, construction digital transformation, Techno-centric digital transformation, construction digital transformation,* and *business model-centric digital transformation.* We then gave insights based on these different themes. By combining bibliometric analysis with topic modeling, we avoid subjective biases associated with human-dependent literature reviews. However, our findings are inevitably influenced by our selection of keywords and restricted to the coverage of the WoS database.

There are, therefore, some limitations to this study. First, only literature from the WoS database and JCR Q1 journals was reviewed and summarized. Also, the scope of this study is limited and focused on DT in advanced manufacturing and engineering and English-language papers. In the future, a broader and in-depth review of DT studies could be extended by our demonstrated methods using both informetric analysis and ML. Papers in different languages, such as Japanese, Russian, German, and Chinese, might be considered and compared.

Moreover, this review is based on existing research results (published and in-press articles); we have not included ongoing and unpublished knowledge. Despite these shortcomings, this study helps clarify the structure and development of DT research in advanced manufacturing and engineering and suggests directions for further research in this critical field.

We believe that DT will be a far-reaching and highly integrated interdisciplinary research field in the academic and practical areas in the future, given the latest development of digital technology. This article has conducted a broad and in-depth discussion of DT in advanced engineering and manufacturing and forwarded all aspects of fundamental knowledge to effectively carry out DT. We hope that our discussion and research agenda can intensify and promote more scholars' research on

Table 2
Summary of research topics, research agenda, and potential research project areas.

Research topics	Research agenda	Potential research project areas
Smart factory	Explores the rising background of smart factories and their advantages compared with the traditional factories.	• Investigate the different interpretations of DT in both factory and smart product-service systems. • Investigate the changes caused by the transformation of smart factories at all levels of the supply chain. • Explore how DT affects new market positions, supply chain networks, operations, and productions.
	Provides exemplars of enabling technologies and high-tech equipment and how they are applied in the smart factory.	• Investigate plurality of use cases for more digital applications, software systems, ICPS, smart product-service systems, and AI-aided manufacturing systems in different fields. • Research the level of integration of network systems required in smart factories for communication and sharing of information. • Research issues regarding security implementation in smart factories.
	Proposes solutions for the technical bottleneck of smart factory applications.	• Research simulation models of the ML-based and cloud-based ICPS that are relevant to digital twins. • Develop a proof-of-service scenario for further empirical implications.
Sustainability and product-service system	Explores the integration of digital transformation and sustainable development.	• Explore the DT-driven circular economy business model considering different levels, relationships, dynamism, and contextualization.
	Explores the various sustainable functions designed for DT and the complex relationships between them.	• Investigate how to bring the right economic, environmental, and social sustainable value and take care of the inequality impacts on enterprise DT, industrial DT, and social DT. • Conduct research into how to make useful and incentive policies to carry out effective digital transformations in industries.
	Explores how we can reduce the resistance to DT and sustain employees' careers.	• Research the mitigating resistance to change how workers' careers can be sustained.
Construction digital transformation	Discusses the dilemma and uncertainty of DT in the construction industry. Encompasses studies of functional, scenario-oriented, data-oriented DT in the construction industry and the implementation path.	• Explore the sustainability and diffusions of BIM patterns. • Study how to use emerging technologies and other possible change dynamics to achieve continuous performance and carry out future and in-context scenarios.

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Table 2 (*continued*)

Research topics	Research agenda	Potential research project areas
	Explores the DT evolutions and transformations from the Construction 3.0 era to Construction 4.0 era (Industry 4.0 in the construction industry).	• Design and develop BIM construction services driven by the IoT, big data, AM, 3D printing, and blockchain.
Public infrastructure-centric digital transformation	Explores the effects of DT in different areas from a public social system perspective	• Develop a methodology to assess digital readiness and ensure better robustness of the public ecosystem while launching DT.
	Explores how the public social system can better respond to DT to maximize the effectiveness of the change and upgrade.	• Investigate how to capture and predict ambiguous and unpredictable public users' dynamic requirements for different public service domains and design acceptable user requirement-centric, performance-centric DT scenarios. • Develop and build a technological or managerial framework in a new public or industrial DT scenario.
	Explores how to evaluate the degree of readiness or maturity for DT and design a foresighted and future DT model in specific scenarios.	• Research the DT maturity model for smart factories, smart operations, smart product-service systems, and data-driven service systems. • Create Industry 4.0 infrastructure and big data maturity models to evaluate and compare DT readiness in different countries, cities, or organizations. • Develop a readiness information structure to support in-depth competitive strategies for market penetration, city development positioning, and workforce impact responses.
Techno-centric digital transformation	Provides exemplars of the application scenarios of digital technologies in various fields.	• Investigate models to integrate edge computing, fog computing, and cloud computing to address the bandwidth limitation and latency issues.
	Introduces the impetus of digital technology and socio-economic factors in accelerating the DT process.	• Develop models to deal with reconfiguration and optimal re-parameterization in CPSs. • Analyze current readiness and barriers for the broader uptake of smart technologies from a practitioner's perspective.
	Discusses state-of-art digital technologies and the breakthrough of specific digital technology, such as CPS, the IoT, cloud services, and big data technology.	• Investigate the integration of smart products with e-services to create a smart product-service system that can enhance customer experience. • Create systems to develop long-lasting relations with consumers.
Business model-centric digital transformation	Explores the internal and external drivers of or barriers to DT.	• Identify enablers, technologies, and capabilities that are required to empower DT efforts in different sectors/domains.
		• Discover digital technologies and data that help the firm resolve its problems and promote value in different digitalization efforts related to the different manufacturing/service provider value chains for the firm and its customers.
	Investigates the nature of the new business model after the digital transformation of enterprises or industries.	• Conceptualize new DT business models through new product-as-a-service, smart product-as-a-service, servitization, or public service models in different sectors with in-context domain knowledge. • Investigate how firms design and implement new operating business models, considering organizational and managerial processes to effectively drive the evaluable and feasible transformations and create new value for short-term, middle-term, and long-term competitiveness.
	Explores the evaluation and measurement of impacts and enhancements of the new business model generated by DT that can bring about organizational performances.	• Develop effective methods or frameworks to evaluate the DT business model from as-is challenges to to-be opportunities. • Identify suitable evaluation criteria or factors (except for financial and benefit perspectives), such as the upgrade and transformation of culture, strategy, organization, leadership, core competence, supply chain business processes, market share or market position. • Explore new DT-based marketing and R&D strategies based on digital platform-driven inputs that are obtained from multiple users' cocreation, crowdsourcing, crowd-sentiment, and engagement.

DT in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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