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- Business - Management and Organization / Araştırma Makalesi / Research Article -

Diagnosing Core Topics in Digital Transformation Studies via Topic Model Approach

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ABSTRACT

The field of digital transformation continues to develop and expand rapidly due to technological advances. This study uses text mining techniques to analyze 5280 articles published between 2014 and 2024 using the LDA model and the Gibbs sampling method, the study identifies the most prominent topics on digital transformation research. Traditional methods, which rely on predefined categories and subjective judgment, are inadequate for identifying underlying themes in large datasets. The study identifies the most prominent topics in digital transformation research and tracks trends by tracking changes in topic rankings across different periods. It also explores sub- specialization areas across 1065 digital transformation journals and assesses how shifts in these areas impact the broader topic landscape. The findings provide valuable insights for practitioners, researchers, journal editors, and policymakers involved in digital transformation.

Keywords: Digital Transformation Research, Text Mining, Topic Model Approach.

Dijital Dönüşüm Çalışmalarındaki Temel Konuların Topik Model Yaklaşımı ile Belirlenmesi

ÖZ

Dijital dönüşüm alanı, teknolojik ilerlemelere bağlı olarak hızla gelişmeye ve genişlemeye devam etmektedir. Bu çalışma, LDA modeli ve Gibbs örnekleme yöntemini kullanarak 2014-2024 yılları arasında yayınlanan 5280 makaleyi analiz etmek için metin madenciliği tekniklerini kullanmakta ve dijital dönüşüm araştırmalarında en öne çıkan konuları belirlemektedir. Önceden tanımlanmış kategorilere ve öznel yargılara dayanan geleneksel yöntemler, büyük veri kümelerinde altta yatan temaları belirlemek için yetersiz kalmaktadır. Çalışma, dijital dönüşüm araştırmalarında en öne çıkan konuları belirlemekte ve farklı dönemlerdeki konu sıralamalarındaki değişiklikleri takip ederek eğilimleri izlemektedir. Ayrıca 1065 dijital dönüşüm dergisindeki alt uzmanlık alanlarını araştırıyor ve bu alanlardaki değişimlerin daha geniş konu manzarasını nasıl etkilediğini değerlendiriyor. Bulgular, dijital dönüşümle ilgilenen uygulayıcılar, araştırmacılar, dergi editörleri ve politika yapıcılar için değerli içgörüler sağlamaktadır.

Anahtar Kelimeler: Dijital Dönüşüm Araştırması, Metin Madenciliği, Topik Model Yaklaşımı.

1. Introduction

Digital transformation (DT), characterized by uncertainty and creative destruction, has gained momentum over the last 20 years through technological and digital innovations. It involves organizations responding to environmental changes using digital technologies like mobile computing, artificial intelligence, cloud computing, and the Internet of Things (IoT) to change value-creation processes. In this period of the second largest and fastest change in human history, no institution, no sector, or organization can isolate itself from DT (Vial, 2021).

Despite the growing strategic relevance of DT, the academic literature on digital change lacks a common consensus on the phenomenon and it encompasses, the different contexts and application areas of DT (Hanelt, Bohnsack, Marz, & Antunes Marante, 2021, p. 1160). This study is important as all

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organizations are affected by this transformation and must adapt to it. Systematic literature reviews can advance existing knowledge, but they can be criticized for being conducted with limited samples.

Company executives prioritize DT at the micro level, while organizations and governments must act at the meso and macro levels to stay ahead of global transformation. According to Zaoui and Souissi (2018, p. 1), DT should be viewed as an economic growth model, influencing all conceptual components that might directly or indirectly influence digitalization, regardless of sectoral limits. Many companies and sectors remain in the early phases of DT due to a lack of comprehensive understanding of the current literature (Schallmo, Williams, & Boardman, 2017).

The study aims to evaluate DT phenomena in scientific journals, identify research trends, most frequently examined themes, and critical challenges, and develop an agenda for future research. It incorporates LDA and Gibbs Models into the TMA, a text mining methodology. The findings reveal the *top 20* most frequently mentioned topics in DT literature over the last decade, research trends, intensively studied topics, and topics that have lost popularity. The study examines a larger number of articles than the current literature, providing more in-depth insights into the phenomena holistically. The study also highlights the growing or diminishing popularity of the examined themes and the direction and continuity of information flow.

Bibliometric analyses of the literature on digital transformation and traditional methods based on predefined categories and subjective judgments are insufficient to identify underlying themes in large datasets. Previous bibliometric analyses often use co-citation or co-word metrics to measure relationships between articles or keywords, and present similar themes in clusters (Pizzi et al., 2021; Shi et al., 2022). These methods fall short in uncovering latent thematic structures in large textual corpora. In this context, it is important to take a more comprehensive assessment of the digital transformation phenomenon, which has been developing at a massive pace over the last decade (Kraus et al., 2021). The study is also important in identifying the topics and terms that are on the rise and on the decline in the digital transformation field. Despite this importance, it has been observed that no evaluation has been made within the framework of the topic model approach, which is a new research method in the literature. This approach enables the identification of hidden thematic patterns, trending and declining topics, and key terminology across the last decade of DT literature. Within the framework of the research questions determined with the support of the literature, a holistic evaluation of the phenomenon was made and 50 terms and 20 most frequently mentioned topics related to digital transformation were identified.

This study advances the literature by providing a comprehensive assessment of the digital transformation phenomenon, which is of critical importance for today's businesses, using the Topic Model Approach, which can be defined as one of the computational social science approaches. Furthermore, the findings are supported by examples from current literature, both theoretical and applied, and reveal potential research gaps for future research. And also, the DT in the examined articles is not limited to individual enterprises or industries but represents a larger ecosystem.

The research is divided into six chapters, focusing on DT, the Topic Model Approach (TMA), and data gathering in DT journals. It also assesses local and global literature on digital transition, discusses the TMA, identifies suitable journals for DT and data gathering, and uses computer-based content analysis techniques to identify *50 common terms* and study areas in DT journals. The study's limitations and merits are also discussed, and future research directions are suggested.

2. Literature on DT

DT is a growing research field involving the widespread adoption of digital technologies in society, industries, and corporate governance (Shi, Mai, & Wu, 2022, p. 1). It significantly impacts production, life, and governance, and is reflected in countries' governance models. Countries like Singapore, China, Taiwan, and South Korea are adapting to this new phase of scientific, technological, and industrial revolution (Huiqian Li, 2024; R. Li, Rao, & Wan, 2022; Qin & Qi, 2021; Yang, Li, & Xie, 2024). This transformation is just beginning to gain momentum in institutions, and is gaining momentum in countries like Türkiye (Avaner & Çelik, 2021; Balli, 2022).

DT is crucial for businesses as it helps them develop strategies, adopt transformation, and gain a competitive advantage. By adopting DT strategies that provide better operational performance, businesses can differentiate themselves from competitors while maintaining quality and service (Barca & Esen, 2012, p. 97; Döven & Gürpınar, 2007, p. 174). Competitive advantage refers to the conditions that allow a company to produce goods or services of equal value at a lower price or in a more desirable way (Porter, 2008). This leads to increased sales or superior margins compared to market competitors. The main focus of DT is to use the latest technologies to improve customer experience, increase working efficiency and productivity, and reduce operating costs and save resources.

Businesses that embrace DT seek to digitize everything they can, including collecting enormous volumes of data from various sources, using digital technology to strengthen the network connecting diverse business processes, creating efficient consumer interfaces, and exchanging information (Nasiri, Ukko, Saunila, & Rantala, 2020, p. 3).

DT is about the changes that digital technologies can bring about in a company's business model, which can lead to changes in products or organizational structures or automation of processes (Hess et al., 2016, p. 124). Companies engaged in DT will provide staff autonomy in upgrading their operations and inventing innovations, encouraging them to take the initiative. Thus, companies at the forefront of DT will gain much more authority, trust, and respect from customers (Zhou, 2019, p. 6). The literature also discusses the role of DT in the transition to flexible organizational designs and digital business ecosystem (Hanelt et al., 2021, pp. 1168-1172), technology infrastructure and current level of innovation (Omrani, Rejeb, Maalaoui, Dabić, & Kraus, 2022), the need for resources to adopt and realize fundamental transformation (Omrani et al, 2022), knowledge management and processing capability (Lakemond, Holmberg, & Pettersson, 2020), digital networking (Verhoef et al., 2021) alignment (Kammerlander, König, & Richards, 2018), and a “mind-set” change (Neeley & Leonardi, 2022) that will involve all management processes of the business, such as radically changing the corporate strategic vision (Niemand, Rigtering, Kallmünzer, Kraus, & Maalaoui, 2021).

Huanli Li, Wu, Cao, and Wang (2021) consider organizational awareness of DT as a prerequisite for technology transition. Businesses that are aware of the phenomenon will gain organizational agility and take part in the transformation process (Alnuaimi, Singh, Ren, Budhwar, & Vorobyev, 2022) by changing the technology they use before their competitors, changing their value creation processes, and taking part in structural and financial change. For these reasons, we focused on the literature on the DT process for businesses.

DT literature studies have been conducted in various directions and methods. Effective studies counting the number of publications and citations in a single journal have made various attempts to identify the intellectual foundations of DT, including journals and authors (Kraus et al., 2021; Vial, 2021; Zaoui & Souissi, 2020). There have been several studies that consider DT from the perspective of small businesses (Garzoni, De Turi, Secundo, & Del Vecchio, 2020; Pelletier & Cloutier, 2019; Stich, Zeller, Hicking, & Kraut, 2020; Ulas, 2019), business models (Berman, 2012; Kotarba, 2018; F. Li, 2020; Vaska, Massaro, Bagarotto, & Dal Mas, 2021), DT maturity and maturity level (Bumann & Peter, 2019; Gollhardt, Halsbenning, Hermann, Karsakova, & Becker, 2020; Kırmızı & Kocaoglu, 2022).

DT has also been addressed in terms of business sustainability (Melo et al., 2023), digital leadership (Martins, 2019; Rosenbloom, 2000), creating new business models and processes or changing existing ones (Frank, Dalenogare, & Ayala, 2019), or using digital technologies to support the transformation of organizational structures, resources or relationships with internal and external actors (Plekhanov, Franke, & Netland, 2022, p. 821). Hanelt et al. (2021, p. 1159) derived four perspectives on the phenomenon of DT. These include technological influence, segmental adaptation, systemic transformation, and holistic co-evolution.

Warner and Wäger (2019) studies reveal that digital transformation is a continuous and technologically based organizational process that is shaped by the factors that affect the development of dynamic capabilities based on the experiences of senior managers and strategically transforms the business model, collaboration and cultural renewal through agility. The study findings are integrated with digital transformation, especially by taking into account the sensing, seizing and transforming measures, which are the main elements of dynamic capabilities, and are consistent with the general literature findings (Bağış et al., 2022; Karadağ et al., 2024; Khurana et al., 2022; Saeedikiya et al., 2024). Matarazzo et al. (2021) reveals that Italian SMEs, digital transformation, enabled by dynamic capabilities such as sensing and learning, drives business model innovation and new value creation for customers through enhanced distribution and delivery channels.

Ellström et al. (2021) studies identify six key organizational routines, rooted in sensing, seizing, and reconfiguring capabilities, that guide firms in structuring and implementing digital transformation through strategic planning, infrastructure alignment, and project decomposition. It is possible to find many studies in the literature that evaluate the phenomenon of digital transformation within the scope of dynamic capabilities as a theoretical basis (Civelek et al., 2023; Soluk and Kammerlander, 2021).

The digital transformation journey, which gained momentum with the widespread use of internet technology in the early nineties, began to be addressed in the literature within the framework of the digital transformation of traditional businesses (Andal-Ancion et al., 2003). The phenomenon of digital transformation, which could be considered revolutionary in those years, began to rise rapidly. Zhu et al. (2006) study develops an integrative model, based on diffusion of innovation theory and the technology–organization–environment framework, to explain the factors influencing post-adoption stages of enterprise digital transformation, emphasizing how digital technologies reshape activities across the value chain to enhance coordination, efficiency, and value creation. An example of this study highlights the critical role of information systems research in advancing health IT (HIT) by addressing design, implementation, impact measurement, and scope expansion, urging scholars to contribute to the transformation of healthcare systems through IT-enabled value across the healthcare value chain (Agarwal et al., 2010). Liu et al. (2011) study presents a pioneering framework in the resource fit domain, illustrating through a practical case how aligning organizational resources supports the nuanced development of digital transformation across the value chain.

It is possible to evaluate the digital transformation phenomenon, which is theoretically diversified and spread across different journals and theoretical frameworks, with many different theories. However, it is not expected to effectively capture hidden issues from large volumes of academic data based on separate assignments based on subjective judgment with predetermined categories of the DT phenomenon studied in these diverse fields. Therefore, to address this gap in the literature, the "Topic Model Approach", a relatively new and recent approach, was adopted in this study.

3. Topic Model Approach

This research aims to address DT through the TMA, a machine learning approach used in social sciences. TMA is different from discrete assignments in existing systematic literature reviews, which are based on subjective judgments and classified according to a single category. It reduces researcher-induced classification error to almost zero and reveals new and emerging topics without the need for any prior categorization. TMA is a computer-based content analysis approach that uses algorithms (Maier et al., 2021) to automatically identify relevant themes in a large, unstructured collection of texts. Examining journals in a particular research area helps identify interviews, theories accepted, research conducted, and tools created (Chen, Zou, & Xie, 2020, pp. 693-694). The study's significance lies in its ability to reveal new and emerging topics without the need for prior categorization.

TMA is a generative probabilistic model with three analytical levels: a body of documents, specific papers within the body, and individual words from each text. It interprets and classifies subjects in a text, eliminating irrelevant words like minor words and grammatical aspects. However, hand-coded textual data sources have two drawbacks: they limit the amount of material that can be evaluated manually in big comparative analyses, and they can only address one theme or topic in an article (Beelen et al., 2017).
Bibliometric approaches use co-citation or co-word measures to quantify associations between articles or keywords, organizing similar themes into clusters (Bağış, 2021; Y. Liu et al., 2021). This analysis investigates article and citation trends, prolific writers, journal connections, regional distributions, scientific collaborations, and research topic evolution. The model used in this analysis differs from previous research, which primarily focused on keywords. By including abstracts from 5.280 publications,

the study's breadth and volume are expanded, while the quality of results is enhanced. This study was not conducted using traditional bibliometric analysis methods. As stated in the abstract, traditional methods based on predefined categories and subjective judgments are insufficient to identify underlying themes in large data sets. The study has the potential to contribute to the field by addressing the digital transformation literature with a relatively new bibliometric method, especially with a distance-based statistical method. Graph and network-based methods such as Vosviewer focus on co-citation, co-author and co-words. This study determines the most prominent topics in digital transformation research and tracks trends by following changes in subject rankings in different periods. Thats why the topic model approach was preferred in this study.

Bibliometric mapping, or scientific mapping, is a significant trend in bibliometrics, allowing researchers to trace a scientific field, define its cognitive structure and evolution, and express its spatial representation of disciplines, fields, researchers, and individual documents (Cobo, López-Herrera, Herrera-Viedma, & Herrera, 2012, p. 1609).

This study employs text mining techniques (Grimmer & Stewart, 2013), specifically in the context of TMA, using LDA and the Gibbs model, to analyze data on DT. The goal is to provide insights into DT practices across contexts, reveal relationships between ideas and topics, and potentially uncover new research avenues on DT.

TMA is a statistical model that uses unsupervised machine learning algorithms to identify and distribute "topics" in a document based on word frequencies and co-occurrences. It's an automatic content analysis method that interprets document content based on given questions (Lesnikowski et al., 2019, p. 2; Neuendorf, 2017, p. 1). The methodology section of the study provides detailed descriptions of selection procedures, labeling, and other procedures for data and target journals.

4. Method

This section discusses the methodology of textual data analysis (TMA), including target journals, data collection strategy, text preparation, topic selection, and labeling procedures. It also discusses the reliability and validity of using computer-based content analysis techniques like LDA and Gibbs. LDA is a method for detecting and defining underlying theme patterns in text documents, allowing topic semantics to be fully described within the Bayesian statistical paradigm (Blei, 2012). It extracts hidden content variables, known as themes, which provide a comprehensive representation of a text collection, allowing subjects to be extracted without prior knowledge (Maier et al., 2021, p. 2).

The LDA algorithm's randomized processes significantly impact the retest reliability of a topic model, as the process is empirically disciplined. This means that no topic model can effectively reduce data if the data is not suitable for answering analysts' questions (DiMaggio, Nag, & Blei, 2013, p. 603).

The majority of studies on DT have been conducted using co-citation and/or citation analysis and depicted as article networks (Kwilinski, 2023; Machado, Duarte, Amaral, & Araujo, 2022; Pizzi, Venturelli, Variale, & Macario, 2021; Purwanto, Wibowo, & Rahayu, 2023). Furthermore, numerous studies in the literature in recent years have ranked DT-related journals based on citation analysis (Hausberg, Liere-Netheler, Packmohr, Pakura, & Vogelsang, 2019; Khoshroo & Talari, 2023; Marino-Romero et al., 2024).

TMA is a valuable tool in DT research, offering advantages over clustering techniques. It is particularly useful in exploratory research where little is known about the data set and researchers are interested in discovering unknown patterns or trends (Lesnikowski et al., 2019, pp. 2-3). TMA is also useful for governments, businesses, and academics in identifying and tracking difficulties in emergent phenomena within a scientific discipline (Small, Boyack, & Klavans, 2014, p. 1450; Wang, 2018).

This study seeks answers to the following questions from the literature on DT:

- What are the most frequently studied topics in DT literature?
- What are the most frequently used terms in DT literature?
- What is the distribution of topics in the DT literature?
- What are the rising and declining topics in DT literature?
- What is the distribution and trend of keywords in DT literature?
- What are the most influential publications and journals?

In the process of creating the data set to answer the research questions, a total of 4.136 records were obtained from the Scopus database with the "TITLE-ABS-KEY ("digita* transfor*") AND DOCTYPE (ar OR re) AND SUBJAREA (busi OR mana) AND LANGUAGE (english) AND PUBYEAR> 2013 AND PUBYEAR <2025" query. Similarly, 4582 records were accessed using the "(((TS= (DİJİTAL TRANSFORMATION)) AND DT= (Article OR Review)) AND WC= (Business OR Management OR Computer Science, Software Engineering)) AND LA=(English)) AND PY= (2014-2024)" query from the Web of Science (WOS) database.

The study analyzed Scopus and WOS data to create a data pool of 8.718 records, which was then reduced to 6.755 using Python. Only the 6.755 records with the precise word "digital transformation" were selected for the study. This was done by extracting articles from the Abstract, Author Keywords, and Keywords Plus fields using R, resulting in a final dataset of 5.280 records. The study aimed to understand the relationship between DT and other fields in the digital landscape.

The number of publications on DT has significantly increased over the years, starting with 3 in 2014 and increasing to 21 in 2016. This growth was accelerated in subsequent years, with 35 publications in 2017 and 91 in 2018. The trend continued to rise in 2019, with 233 publications and continued to soar in 2020 with 380 publications. The peak of academic focus was seen in 2021, with 616 publications, followed by 914 in 2022. This momentum continued in 2023 and 2024, with 1.405 and 1.576 publications respectively, highlighting the importance of DT in addressing contemporary challenges and opportunities. The average rate of increase is approximately 0.972.

$$\frac{1 + 2.5 + 0.67 + 1.6 + 1.56 + 0.63 + 0.62 + 0.48 + 0.54 + 0.12}{10} \approx 0.972$$

Between 2014 and 2024, Google Trends searches revealed similar results on DT. Figure 1 presents a worldwide search density map and growth rates from Google Trends and our dataset.

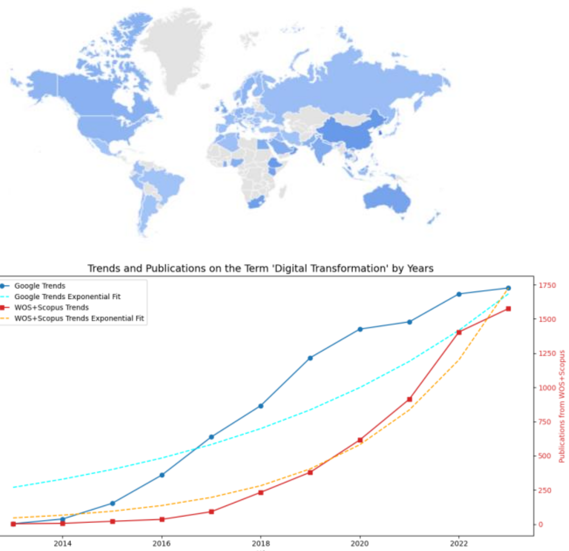

Figure 1. Subject Browsing Density Map and Google Trends and Publication Counts
Source: Created by the authors

The study reveals that DT studies have grown similarly to Google Trends' data, with the topic being extensively searched in Singapore, South Korea, Hong Kong, UAE, and Malaysia, as indicated by the evaluation through GeoMap. The filtering process for data set creation is also presented in Figure 2.

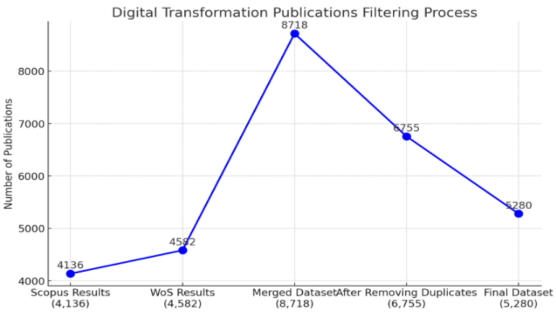

Figure 2. Filtering Process Related to Creating the Data Set
Source: Created by the authors

A dataset of 1065 journals on DT was analyzed, with 15 journals having the highest number of publications on a yearly basis. As seen in Figure 3, the journals that publish the most on DT and related fields and the number of publications is as follows: Technological Forecasting and Social Change, the leader in this field, focuses on forecasting and societal impacts of technological advances. The Journal of Business Research, second in this field, emphasizes the intersection of business strategies and DT. Finance Research Letters, the second in this field, focuses on financial aspects. IEEE Transactions on Engineering Management, the third in this field, addresses innovative engineering and management issues.

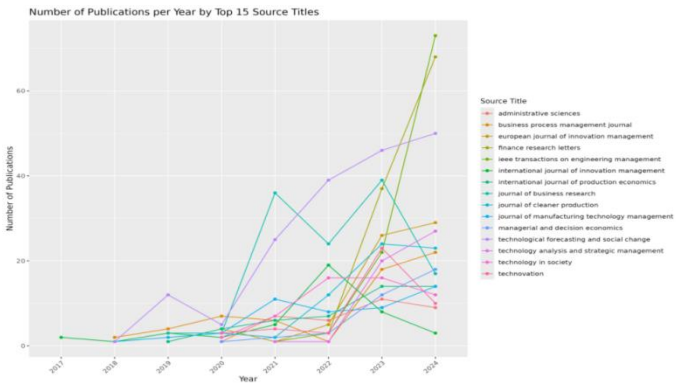

Figure 3. List of the 15 Most Published Journals
Source: Created by the authors

Among journals with lower publication numbers but significant contributions, the European Journal of Innovation Management and the Journal of Cleaner Production (66 publications each) examine innovation processes and sustainable practices. The Business Process Management Journal (60 publications) focuses on organizational processes, while Technology in Society (53 publications) explores the societal aspects of technology. Technology Analysis and Strategic Management (49 publications) and International Journal of Production Economics (46 publications) contribute to the understanding of strategic and economic dimensions.

In addition, the Journal of Manufacturing Technology Management (46 publications) and the International Journal of Innovation Management (43 publications) highlight critical roles in manufacturing and innovation management. Technovation (43 publications) focuses on innovative solutions, while Administrative Sciences and Managerial and Decision Economics (34 publications each) address management and decision-making in the context of DT. These journals provide essential resources for understanding the multidimensional nature of DT.

The study utilized text mining and topic modeling technologies to analyze scholarly papers on DT. The most frequently used term in the literature is "digital," which is central to discussions about technological and institutional changes. The term "transformation" emphasizes the importance of adapting to digital advancements. Business-related terms like "business" and "industry" highlight the practical applications and organizational implications of DT. Technical innovations driving change are highlighted by terms like "technology" and "technologies." Performance, development, and impact are important terms for evaluating digital initiatives' outcomes. Analytical methods are highlighted by terms like "data," "analysis," and "model." Other notable terms include "digitalization," "framework," and "adoption," indicating efforts to conceptualize and implement digital strategies. The prominence of "value," "capabilities," and "knowledge" reflects a focus on building competencies to leverage DT effectively.

Studies often employ the most probable words for each subject to identify a label that accurately represents the topic's fundamental substance, aiming to establish topic-level semantic validity, a crucial aspect of semantic validity (Maier et al., 2021, p. 13; Quinn, Monroe, Colaresi, Crespin, and Radev (2010), p. 216).

The text analysis utilized TF-IDF and DTM (Du, Ge, Yao, Chen, & Xu, 2023; D. Kim, Seo, Cho, & Kang, 2019; S.-W. Kim & Gil, 2019) to analyze the frequency and importance of words. The TF-IDF matrix was converted into a data frame, and each word's TF-IDF score was calculated to estimate its relevance level. The top 10 frequently occurring words were identified using DTM and their frequencies were calculated. The results were displayed in two graphs, providing a comprehensive understanding of the issue and allowing comparison of terms based on frequency and importance Figure 4.

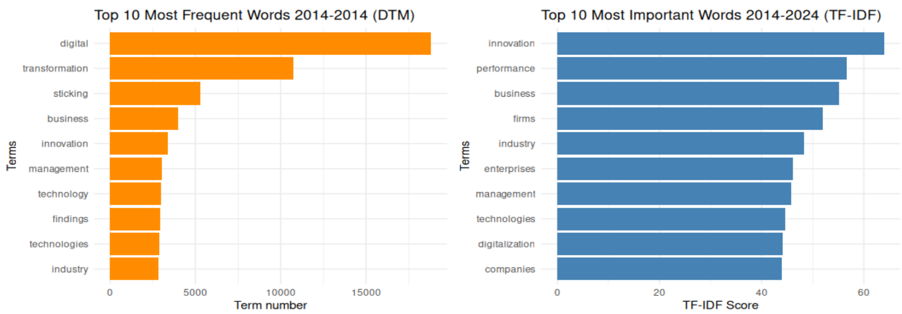

Figure 4. Representation of Keywords with DTM and TF-IDF
Source: Created by the authors

LDA is a statistical model that explains observations with unobserved groups and why some parts of data are similar. It assumes each document is a mixture of several topics, and each word can be attributed to one of them (Bastani, Namavari, & Shaffer, 2019, p. 260). Figure 5 illustrates the dependencies between model parameters.

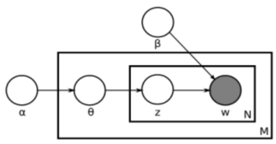

Figure 5. LDA Plate Representation
Source: Created by the authors

LDA model, the relationships and distributions between each document and topic are defined using various parameters. In Figure 5, the symbol M represents the total number of documents, while N represents the number of words in a particular document. The parameter α, which is the Dirichlet before the topic distributions per document, determines the topic diversity that documents can contain. A high value of α increases the probability that documents generally contain a mixture of many topics, while a low value of α indicates that documents tend to cover only a few topics. Similarly, the parameter β, which is the Dirichlet prior on the word distributions per topic, determines the word diversity of a topic; a high β ensures that the topic contains a wide mix of words, while a low value of β ensures that it is limited to a narrower set of words (Bastani et al., 2019; George & Doss, 2018; S.-W. Kim & Gil, 2019).

LDA uses Dirichlet distributions to estimate topic and word distributions (θm, ϕz) for each text. The topic assignment (zmn) of the nth word in a given text is acquired from the topic distribution (θm). The word appropriate for the selected subject (wmn) is derived from the word distribution of the topic (ϕzm). After calculating the amount of words N for each text, this algorithm selects a topic combination for the document and generates N words based on that mixture. The document's topic distribution (zm,n ~ Multinomial(θm)) is used to pick a word (wm,n ~ Multinomial(ϕzm)) (Blei, Ng, & Jordan, 2003). This method is continued until the document's word count reaches the specified topic-mix criterion.

Document-topic distribution is a method for creating new documents by determining the total number of words in a document, selecting a topic mix, and generating words based on the multinomial distribution of the selected topic. This process is repeated N times until the word distribution meets the topic-related criterion. The probability of each document containing a mixture of the most and least topics is determined using parameters α and β, based on the Dirichlet prior and word distribution per topic.

The process of determining the optimal number of topics in a text mining model using the Gibbs sampling method and the LDA is described (Nikita, 2016). Four metrics were used in the model, namely CaoJuan2009, Deveaud2014, Arun2010, and Griffiths2004. CaoJuan2009 measures the consistency of words selected with the highest probability for a given topic, Deveaud2014 measures the logicality and meaningfulness of words in a given topic, Arun2010 measures the separation between words and topics, and Griffiths2004 measures the uncertainty in the distribution of words and separation of topics for a given topic (Arun, Suresh, Veni Madhavan, & Narasimha Murthy, 2010; Cao, Xia, Li, Zhang, & Tang, 2009; Deveaud, SanJuan, & Bellot, 2014; Griffiths & Steyvers, 2004). The optimum number of topics for Griffiths2004 (maximize) and Arun2010 (minimize) was determined as (K=10) as shown in Figure 6.

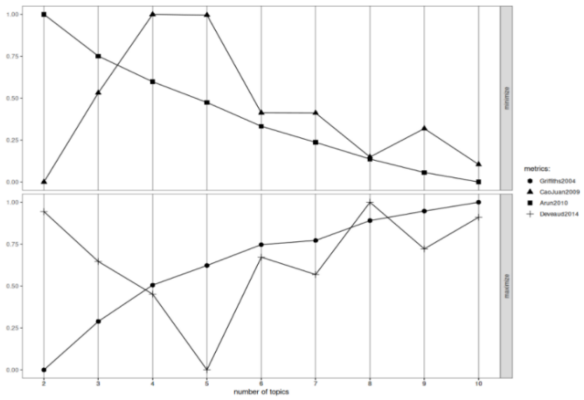

Figure 6. Comparison of Metrics to Evaluate Model Performance
Source: Created by the authors

In the study, 10 DT topics were analyzed and five terms with the highest beta values were selected for each. The Kamada-Kawai method was used to visualize the common terms in Figure 7, and a comprehensive analysis is provided by presenting the content and categorization of these topics in Table 1.

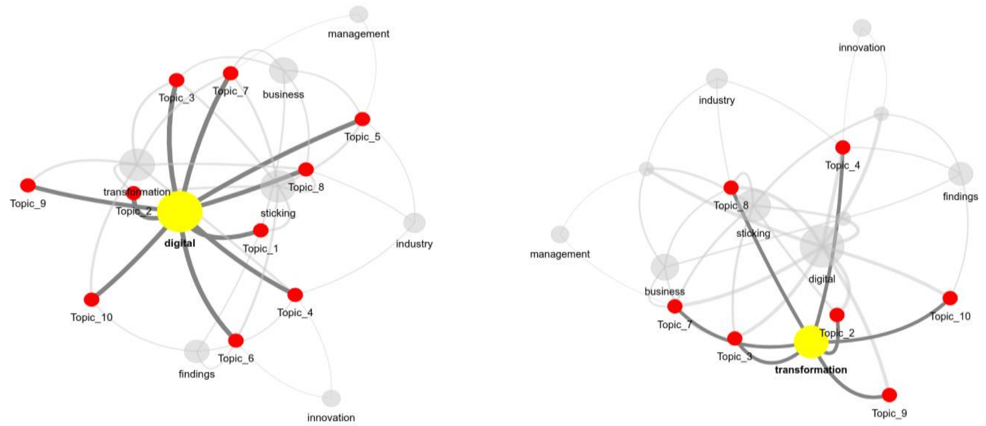

Figure 7. Demonstration of Topic-term Relationship
using the Kamada-Kawai Method (visNetwork with R)
Source: Created by the authors

Table 1. Contents and Categorization of Topics

Topics	List of TopicTerms Generated with LDA (Topic=10, Term=5)	Categories Derived from Lists of Topic Terms
Topic_1	Digital, sticking, business, findings, performance	DT and Business Performance
Topic_2	Digital, sticking, transformation, enterprises, firms	DT in Enterprises
Topic_3	Digital, transformation, business, development, sticking	Business Development and DT
Topic_4	Transformation, digital, innovation, industry, findings	Innovation and Industry in DT
Topic_5	Digital, business, management, sticking, industry	Digital Business Management
Topic_6	Digital, sticking, technologies, findings, innovation	Technological Innovations in DT
Topic_7	Digital, transformation, business, management, sticking	Business Management and DT
Topic_8	Digital, transformation, industry, sticking, business	DT in Industry and Business
Topic_9	Digital, transformation, technology, technologies, process	Technological Processes in DT
Topic_10	Transformation, digital, findings, performance, supply	Performance and Supply Chain Management

Source: Created by the authors

Word clouds are a text mining technique that visually depicts the dominant terms of a given topic. As the frequency of a word increases, its area or text size increases, allowing researchers and readers to quickly identify the most dominant words in specific topics. The wordcloud2 function in the code provides this dynamic and interactive HTML format. The word cloud for Technological Innovations in DT (Topic 6) is presented in Figure 8.

Figure 8. Word Cloud for Technological Innovations in DT (Topic 6)
Source: Created by the authors

The topic distribution was determined using theta values from the gamma matrix and average theta values over the years to track their impact. Results are presented as line graphs in Figure 9, illustrating the changes in each topic over time.

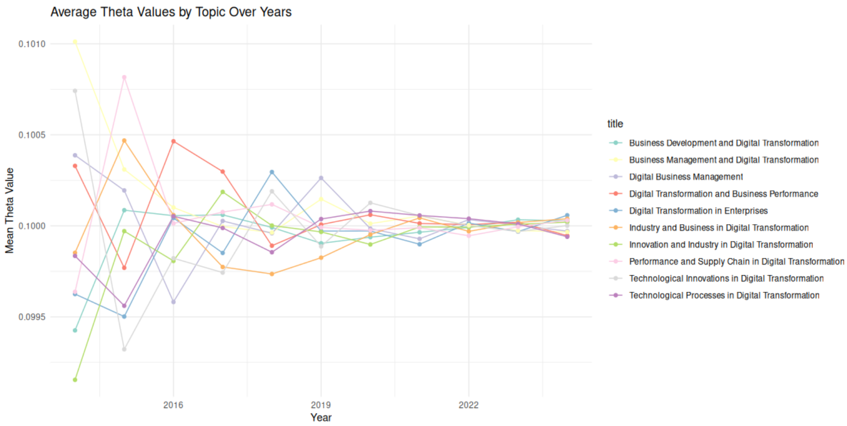

Figure 9. Mean-Theta Plot (K=10)
Source: Created by the authors

A technique was employed to identify and display the most common bigrams in academic paper abstracts, recombining generated words into bigrams and determining their frequencies. Figure 10 displays a bar chart with the ten most common bigrams, providing insights into repeating phrases and topics.

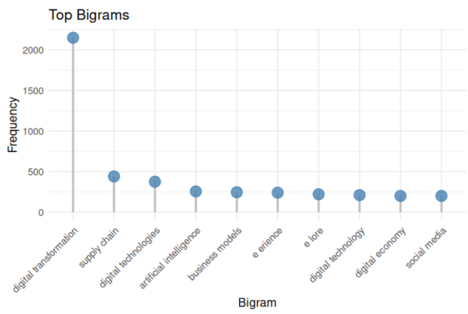

Figure 10. Top 10 Bigrams
Source: Created by the authors

The LDA model's outputs were analyzed using LDAvis, which provided an interactive visualization of the term distribution matrix and document-topic distribution matrix. The data was converted to JSON format for interactive viewing. The serVis function investigated topic-term distributions, allowing for exploration of phrases, commonalities, and most commonly used terms. Figure 11 visually represents the LDA model's outputs.

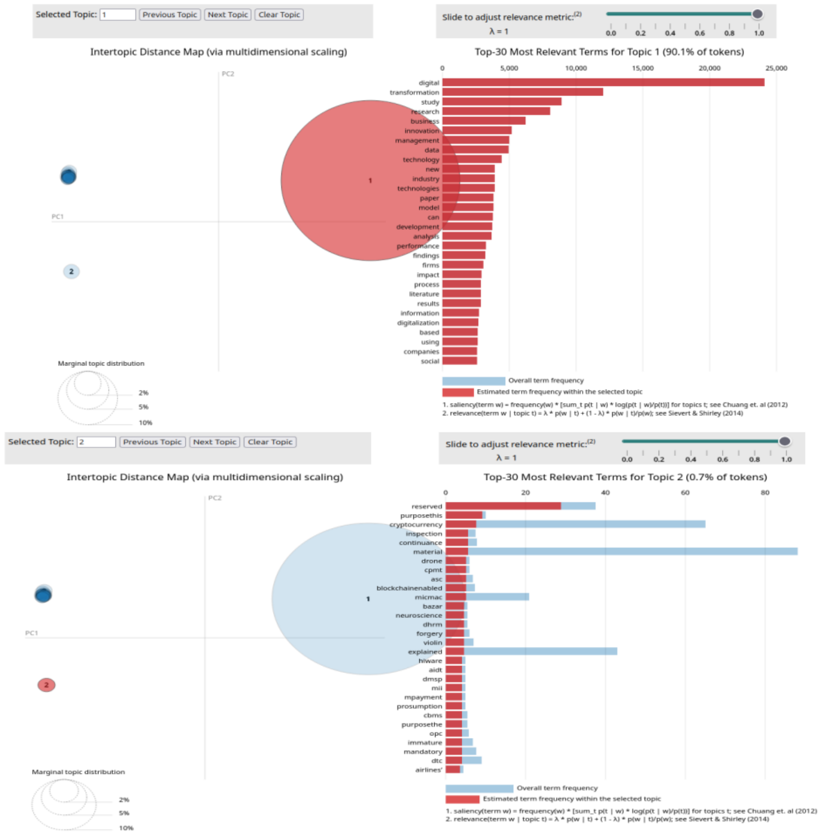

Figure 11. Results of LDA Model
Source: Created by the authors

Topic models were evaluated according to coherence scores and prevalence values, with the top five words chosen for each year. A hierarchical clustering analysis was done, and dendrograms were used to depict topic associations in Figure 12. This research gave insights into patterns in the academic literature on DT and changes over time, using the last four years with the most publications as a reference.

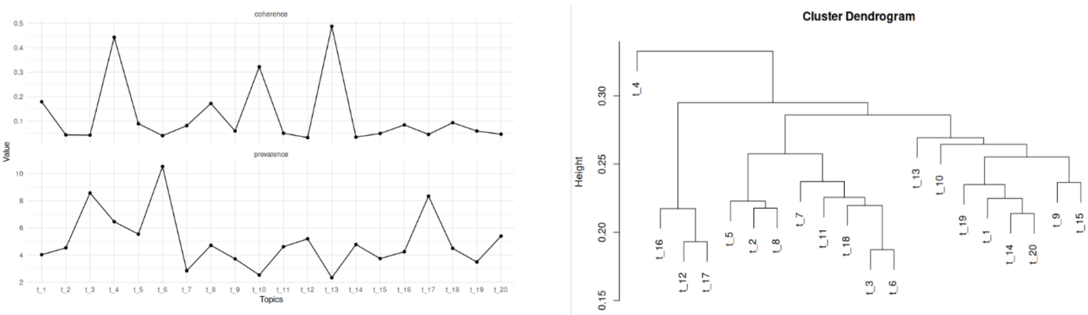

Figure 12. Coherence, Prevalence and Dendrogram Clusters
Source: Created by the authors

The study reveals that subject 13 (t_13) has the highest quality and is closely connected to other terms. However, it has a low likelihood of being distributed in all papers, suggesting that the review may not use the combination of words from Topic 13. The dendrogram uses the Hellinger distance to determine the degree of similarity between the subjects. Topics 3 and 6 show a higher degree of similarity, while Topics 12 and 17 are more similar. The findings, including coherence and prevalence information for the 20 selected topics and 15 terms per topic, are presented in Table 2.

Table 2. Coherence and Prevalence Rates for 20 Selected Topics

Topic	Coherence	Prevalence	Topic	Coherence	Prevalence
t_1	0.179	4.024	t_11	0.050	4.610
t_2	0.043	4.528	t_12	0.032	5.191
t_3	0.042	8.566	t_13	0.488	2.329
t_4	0.443	6.451	t_14	0.034	4.776
t_5	0.089	5.535	t_15	0.049	3.738
t_6	0.040	10.519	t_16	0.084	4.244
t_7	0.081	2.840	t_17	0.045	8.331
t_8	0.172	4.711	t_18	0.093	4.491
t_9	0.059	3.715	t_19	0.059	3.486
t_10	0.322	2.525	t_20	0.046	5.392

Source: Created by the authors

The study employed a Latent Dirichlet Allocation (LDA) model to identify the top 20 topics related to Digital Transformation (DT). The model was trained over 500 iterations with a burn-in period of 180. Dirichlet priors were empirically determined as α=0.1 and β=0.05, and optimize_alpha = TRUE was enabled to allow the model to dynamically adjust the alpha parameter during training. The model's performance was evaluated using various metrics provided by the textmineR package, including log-likelihood, coherence scores, and R-squared. The R-squared value, in particular, was used to assess the proportion of variability in the document-term matrix explained by the topic model, similar to its interpretation in linear regression. High coherence and R^2 scores indicate the semantic integrity and explanatory power of the identified topics.

In the LDA framework, the Dirichlet prior parameters α and β are critical in shaping topic sparsity and distinctiveness (Blei, Ng, & Jordan, 2003). A low α encourages documents to concentrate on a few dominant topics, while a low β promotes more interpretable topics with a narrower and more relevant set of words. The values of α=0.1 and β=0.05 used in this study align with standard practice in the literature (Griffiths & Steyvers, 2004; Mimno et al., 2011) and were also validated empirically based on coherence and model fit metrics.

The topic modeling analysis (TMA) provides methodological details and reveals key themes and discourse patterns in the DT literature. Representative terms for each topic, as shown in Table 3, offer insights into the structure of the thematic space captured by the model.

Table 3. Aggregate and Best Terms on 20 Selected Topics

Topic	List of Topic Terms Generated with LDA (Topic=20, Term=15)	Categories Derived with Generative AI from Lists of Subject Terms
t_1	data, smart, big, big_data, analytics, systems, information, iot, technology, service, use, internet, digital, paper, technologies	DT and Data-Driven Technologies
t_2	dt, study, digital, research, within, insights, sustainable, transformation, digital_transformation, transformation_dt, challenges, sustainability, strategies, findings, management	Sustainable DT and Strategic Management
t_3	digital, transformation, digital_transformation, technologies, new, digital_technologies, firms, innovation, organizational, change, organizations, management, strategic, process, role	Strategic DT and Innovation Management
t_4	sticking, tongue, tongue_sticking, e, e_tongue, erience, sticking_erience, lore, study, sticking_lore, limited, group, sticking_lores, lores, technology	Experiential Interaction and Technology Dynamics
t_5	research, literature, review, analysis, future, digital, literature_review, systematic, future_research, knowledge, digital_transformation, transformation, studies, study, articles	Systematic Review and Knowledge Synthesis in DT Research
t_6	digital, transformation, digital_transformation, companies, new, business, will, technologies, challenges, also, rights, pandemic, article, processes, changes	DT and Adaptation of Businesses in the Post-Pandemic Period
t_7	capabilities, healthcare, dynamic, digital, dynamic_capabilities, health, capability, study, firms, service, innovation, research, organizational, transformation, servitization	Dynamic Capabilities and Digital Innovation in Healthcare Transformation
t_8	study, purpose, findings, research, design methodology approach, originality value, publishing, limited, publishing_limited, emerald, emerald_publishing, paper, implications, practical, practical_implications	Academic Research Publishing and Practical Implications for Academic Studies

t_9	education, digital, employees, skills, human, work, learning, higher, study, employee, students, management, higher_education, educational, resource	Digital Skills Development and Learning in Higher Education and Workforce Management
t_10	supply, chain, supply_chain, blockchain, chains, logistics, study, supply_chains, resilience, sc, food, technology, blockchain_technology, management, digital	Digital Supply Chain Management and Resilience with Blockchain Technology
t_11	business, model, digital, models, value, innovation, business_model, business_models, transformation, maturity, digital_transformation, new, process, case, study	Digital Business Model Innovation and Transformation
t_12	performance, digital, innovation, transformation, firms, digital_transformation, relationship, study, effect, firm, capability, role, impact, data, positive	The Impact of DT on Company Performance and Innovation
t_13	ai, intelligence, artificial, artificial_intelligence, accounting, intelligence_ai, automation, research, paper, cloud, technologies, audit, auditing, management, adoption	AI Adoption and Automation in Accounting and Auditing
t_14	quality, model, management, process, system, proposed, information, based, approach, method, analysis, framework, transformation, systems, digital_transformation	Quality Management and Process Frameworks in DT
t_15	marketing, excuse, media, digital, online, customer, tourism, social, customers, excuse_mecommerce, e-commerce, social_media, study, use, consumer	Digital Marketing and Consumer Behavior in E-Commerce and Tourism
t_16	study, financial, banks, digital, banking, adoption, technology, model, factors, impact, using, structural, performance, equation, transformation	Impact of Digital Banking Technology Adoption on Financial Performance
t_17	digital, transformation, digital_transformation, enterprises, innovation, corporate, effect, enterprise, impact, firms, development, green, companies, Chinese, listed	The Impact of DT and Innovation on Corporate Development in Chinese Enterprises
t_18	digital, transformation, digital_transformation, SMEs, small, leadership, enterprises, factors, study, organizational, research, culture, medium-sized, small_mediumsized, readiness	Leadership and Institutional Readiness for DT in SMEs
t_19	industry, manufacturing, technologies, construction, industrial, adoption, implementation, production, technology, companies, factors, study, bim, barriers, lean	Adoption of Advanced Manufacturing Technologies in Manufacturing and Construction Sector
t_20	digital, development, economy, public, economic, digitalization, countries, level, analysis, ICT, technologies, sector, study, services, information	Digitalization and Economic Development in the Public Sector

Source: Created by the authors

5. Distribution of Topics in DT Research

The study analyzed 20 key subjects in DT literature journals using TMA approaches. It found that studies in the last decade covered topics such as DT, sustainability, innovation management, experiential interaction, technology dynamics, business adaptation post-pandemic, sectoral studies, quality management, Chinese enterprises, and leadership for transformation in SMEs. Business topics included business performance, DT in entrepreneurs, innovation and industry transformation, business management, technological innovations, transformation in industry and business, technological processes and performance, and supply chain management.

6. Conclusion

The study analyzed data from 1.065 journals, 4.136 from Scopus, and 4.582 from Web of Science, resulting in a total of 8.718 articles. The final dataset included 5.280 entries, a departure from previous studies that used similar logic and limited data by industry. However, these studies have been criticized for not providing a comprehensive picture of the research flow. Techniques like area drawing, keyword analysis, density analysis, and location analysis were used for data extraction and quantitative analysis. Current literature addresses DT using methods like systematic literature review (Zaoui & Souissi, 2020), Delphi methodology (Naji, Gunduz, Alhenzab, Al-Hababi, & Al-Qahtani, 2024), DEMATEL (Jafari-Sadeghi, Mahdiraji, Alam, & Mazzoleni, 2023, p. 4), Vosviewer (Shi et al., 2022).

The study aims to provide a comprehensive approach to DT in SMEs, consolidating theoretical and managerial conclusions. It addresses ambiguous language in studies and adds to the existing literature by addressing the complexity of the term. The study addresses the lack of knowledge about entrepreneurs and decision-makers managing the digitization process (Jafari-Sadeghi et al., 2023, p. 1), contributing significantly to the understanding of DT in SMEs.

The study by Browder, Dwyer, and Koch (2024, pp. 128-129) highlights the importance of DT in enhancing organizational resilience during crises (Browder et al., 2024, p. 130). They found that digital capabilities helped firms adapt unexpectedly during the COVID-19 pandemic. Fitzpatrick, Gill, Libarikian, Smaje, and Zemmel (2020, p. 2) also highlight the pandemic as a catalyst for companies to accelerate DT and gain awareness of its multifaceted nature. They emphasize the importance of institutional resilience, digital capabilities, and crisis management during and after the crisis under the title of adaptation.

The existing literature on digitally driven improvements includes creating new business models (Vaska et al., 2021; Verhoef et al., 2021), reshaping operations (Amit & Han, 2017), and creating a new value network by establishing closer connections with customers and suppliers (Berman, 2012, p. 18; Lichtenthaler, 2017; Vial, 2021). The findings of our study align with the literature on digital business model innovation and transformation, emphasizing the importance of shaping operations, creating new business models, and new value-creation processes.

Competitive business success relies on understanding target audiences (Cosa, 2024; S. Lee & Peng, 2023), meeting evolving customer needs, driving growth, and innovation. Entrepreneurial governance is a complex process that involves evaluating and transforming opportunities related to DT (Gomes et al., 2024). This study explores digital business management and DT in enterprises. Firms' ability to cope with uncertainty is crucial for creating new competitive advantages through DT (Nambisan, 2017). The study also examines the effects of DT on firm performance and innovation. Understanding these issues is essential for achieving success in the competitive business landscape.

Previous research has demonstrated that DT is not an automatic and spontaneous process, with organizations encountering conflicts (Furr, Ozcan, & Eisenhardt, 2022), opposition (Poikkimäki, 2023), and setbacks (Björkdahl, 2020; Heavin & Power, 2018). According to the study's conclusions, this problem is addressed during the leadership and organizational preparation phase for DT. Favoretto, Mendes, Filho, Gouvea de Oliveira, and Ganga (2022) define DT as more or less substantial changes to a company's business model, procedures, resources, operational techniques, or culture.

There is a growing literature on how DT also transforms the strategy-making processes of companies (Warner & Wäger, 2019). Some studies address this change in the context of strategic renewal and dynamic capabilities (Ellström, Holtström, Berg, & Josefsson, 2021; Teece, 2019), authors who evaluate it as design thinking (Blanka, Krumay, & Rueckel, 2022; Vendraminelli, Macchion, Nosella, & Vinelli, 2023), and studies that evaluate it within the framework of agile transformation (Gurusamy, Srinivasaraghavan, & Adikari, 2016). In the findings of our study, these issues are addressed under the title of dynamic capabilities and digital innovation in healthcare transformation. Digital technologies are discussed as the pioneer of process integration and dynamic capabilities in healthcare services. Similar findings are also found in the literature (Chakravorty, Jha, Barthwal, & Chakraborty, 2020).

The findings of the study are in line with the general trend of the literature. The study needs to be discussed in terms of its comparison to the bibliometric analyses in the existing literature. In his study on the effects of DT on internal audit, Berman (2012, p. 1) stated that the effects of DT on companies are devastating and found that there are studies on continuous auditing, fraud detection, technological innovation, and data analytics on internal auditing. Marino-Romero et al. (2024, p. 10) found findings under the clusters of the DT process of SMEs, digital technologies, and digital business models among the results of their bibliometric analysis of DT. It is seen that these findings, which are also included in our study, are named with similar names. Similar to the authors' studies, other bibliometric analyses in the literature see DT as a process of combining digital technologies with solid business models to produce great value for businesses (C.-H. Lee, Liu, Trappey, Mo, & Desouza, 2021, p. 1). These authors' articles can be criticized for being relatively limited in number (99 articles) and analyzing the accumulation of knowledge in a limited field (production systems and engineering). The study identifies six key digital transformation topics: smart factories, sustainability, product-service systems, construction, public infrastructure-centered DT, technology-centered DT, and business model-centered DT. Similar findings were found in sustainability, adoption of advanced production technologies, digitalization in the public sector, and economic development in the production and construction sectors.

Kwilinski (2023, pp. 62-63) analyzed bibliometric analysis on DT, focusing on sustainability. He identified clusters such as "Technological support for sustainable urban development in the digital economy," "DT as a way to ensure sustainable enterprise development," "problems of the modern stage of information society development in the context of technological breakthroughs," "impact of DT on sustainable consumption and production," and "DT in agriculture as a way to achieve sustainable development goals.

Our study has some important outcomes that are notable in the findings and not included in the existing literature reviews and not found in bibliometric analyses. These include terms gathered under “experiential interaction and technology dynamics”, sustainable DT and strategic management, DT and data-driven technologies, digital skill development and learning in higher education and workforce management, digital supply chain management and resilience with blockchain technology, digital marketing and consumer behavior in e-commerce and tourism, adoption of digital banking, DT of Chinese enterprises, it is seen that many results have been achieved both in macro and meso dimensions. When the reasons for this situation are considered, it can be justified to complete the study by covering almost the entire field of the research data. The contribution of the study to the field can be shown as providing opportunities for inferences that direct new and original studies under these headings.

The findings are seen as a theoretical migration from other domains, resulting in the concept's extension. This study offers practical consequences for managers in terms of improving technology resources and IT infrastructure, as well as workers' digital abilities, innovation level, and institutional structures, in order to accelerate business DT.

The study's conclusions also address academic and journal editors. It is believed that channeling fresh and unique research towards these newly developing topics, which have remained buried, explored but not properly labeled within the subject of DT, will allow the field and theory to grow. While digital transformation provides businesses with competence in terms of the requirements of the age, there are some challenges that should not be ignored. Digital transformation will lead to the disappearance of routine jobs that people do and do not require much skill, such as automation and artificial intelligence integration (Huang, 2024). This transformation may also cause some negative aspects such as data privacy (Díaz et al., 2021), surveillance and agency costs (Kensbock and Stöckmann, 2021). In addition, not every digital transformation story can be expected to end successfully. Lack of technological infrastructure, digital resistance, strategic incompatibility and people's lack of competence in transformation will affect the success of digital transformation (Borovkov et al., 2021). It is critical to adopt inclusive and sustainable practices to solve these challenges.

Limitations

In data analysis, the filtering process used to account for human preferences in cut-off choices (for example, time periods) has a selection bias due to its purpose and nature. Some important studies may have been neglected. As a result, this study makes no claim to have reviewed all of the material. The thematic framework for identifying subjects and terminology recognizes certain terms but not all of them. The study's limitations include a lack of analytical depth. Furthermore, the raw material obtained is limited in terms of the writers' viewpoints when compared to the literature.

Advantages

This study provides a unique perspective on demand-based demand theory (DT) literature, contrasting with traditional literature reviews that rely on manual coding. It uses a data set not determined in advance and examines most respected journals in the field. The study identifies popular academic topics, areas requiring investment, and promising topics for R&D projects, scientific publications, patents, and grants (Azagra-Caro & Consoli, 2016). It contributes to academia and practice by identifying the antecedents and successors of demand- or supply-based DT. Advantages include a comprehensive evaluation of research flow in respected journals.

Implications for practice and academia

This study offers valuable insights into Digital Transformation (DT) and management practices, highlighting the potential for transitioning to flexible organizational structures. It provides implications for the transformation process in response to global crises. The study also offers managers insights into DT dynamics, aligning with literature on awareness, acceleration, and adaptation of DT potential (Hanelt et al., 2021, p. 1186). These insights help managers understand strategy processes, allocate resources, accelerate the design of new digital processes and products, and develop adaptation skills to integrate new digital products and processes within the organization. Academic studies provide information on DT, helping to identify areas of growth and decline. This holistic view of DT helps academics identify areas of growth and decline in the field. Based on the findings, managers should not only focus on improving their digital infrastructure but also consider integrating specific technologies such as cloud-based ERP systems, AI-powered customer insight platforms, or IoT-enabled supply chain tools. Furthermore, adopting supportive policies like structured digital upskilling programs or data governance frameworks can facilitate more sustainable and organization-wide digital transformation. Businesses can organize pre-information meetings on areas where their technology is intensive and implement practices that will prevent employees from resisting this transformation.

Araştırmacıların Katkı Oran Beyanı / Contribution of Authors

Yazarların çalışmadaki katkı oranları Hüseyin PARMAKSIZ %50/ Osman AKARSU %50 şeklindedir.
The authors' contribution rates in the study are Hüseyin PARMAKSIZ %50/ Osman AKARSU %50 form.

Çıkar Çatışması Beyanı / Conflict of Interest

Çalışmada herhangi bir kurum veya kişi ile çıkar çatışması bulunmamaktadır.
There is no conflict of interest with any institution or person in the study.

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Bu çalışmada Yükseköğretim Kurumları Bilimsel Araştırma ve Yayın Etiği Yönergesi kapsamında belirtilen kurallara uyulmuştur.
In this study, the rules specified within the scope of the Higher Education Institutions Scientific Research and Publication Ethics Directive were followed.

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