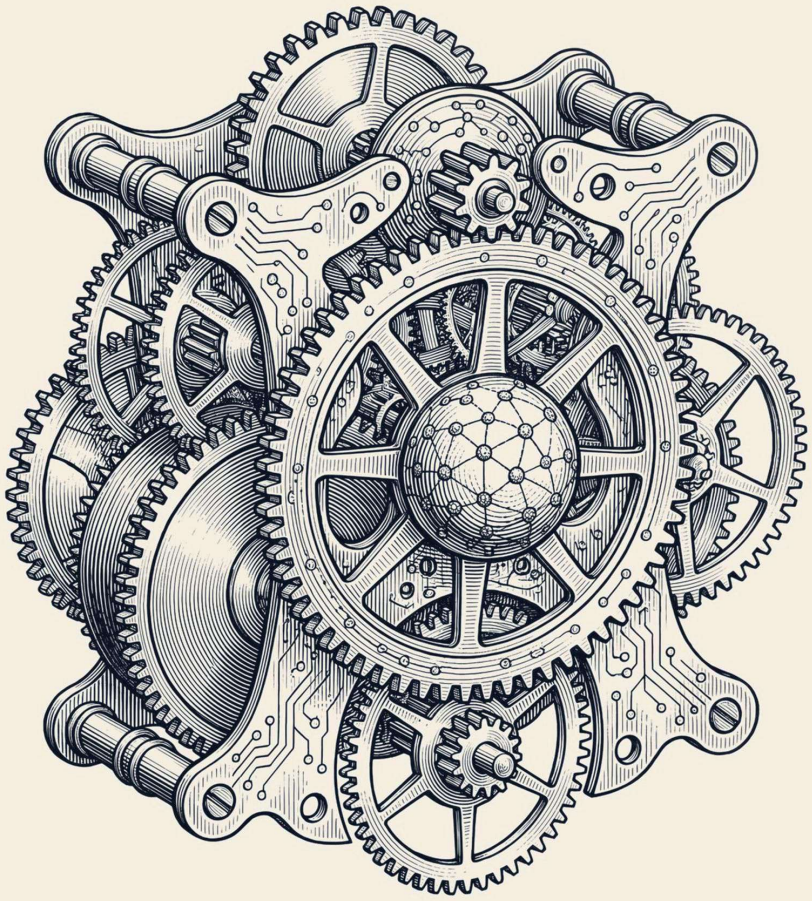
Volume I

Management Information Systems

Redefining Management in the Digital Age



Edited by

ALPER ERTÜRK

MANAGEMENT INFORMATION SYSTEMS
Redefining Management in the Digital Age – Volume I

Edited by
Alper Ertürk

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Preface

This book started with a question. In conversations with students, colleagues and managers, we kept returning to the same one: is artificial intelligence simply making information systems faster, or is it changing what an information system is?

There is no single answer. For a manager, the answer sits at the decision table. For a public servant, it lies in the tension between regulations and digital systems. For a data engineer, it may come down to keeping a data lake from turning into a swamp. For this reason, the book was not built around one point of view but through several perspectives that complement one another.

"MANAGEMENT INFORMATION SYSTEMS Redefining Management in the Digital Age – Volume I" examines, from a Management Information Systems perspective, the transformation that artificial intelligence and data-driven technologies are bringing to information, decision-making, interaction, organizations and governance. Its eleven chapters are the work of researchers at different stages of their careers. The methods range from bibliometric analysis to qualitative case research, and from conceptual model development to quantitative survey research. This variety was kept on purpose, because the field itself has not yet settled enough to be read through a single method.

The book is written primarily for researchers and graduate students working in this area. That said, many chapters offer implications that speak directly to managers and practitioners, and care was taken so that the book can also serve as a supplementary text in MIS courses. Each chapter can be read on its own. Read together, however, they tell a shared story, and the Introduction and Conclusion aim to make that story visible.

As editor, I thank the chapter authors for their patience and contributions. I am also grateful to the reviewers whose comments strengthened the chapters, to the Malton London Press team for their support throughout the publication process, and to my family for sharing with me the time this work required.

I hope this book will be useful to anyone who wants to think about information systems in the age of AI not only as a technical matter but as a question of people, organizations and society.

Prof. Dr. Alper Ertürk
Istanbul Health and Technology University

About Editor

Prof. Alper Ertürk (PhD) is currently working as a Full Professor and the Dean of Engineering and Natural Sciences Faculty at Istanbul Health and Technology University. Prof. Erturk is also affiliated with Australian University – Kuwait, as an Adjunct Professor.

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He has more than 100 publications, which have been cited more than 3000 times. He also successfully secured external funding for multiple research initiatives. During his career, Prof. Erturk achieved to receive many awards including "Outstanding Teaching Award" and "Best Paper Award". He is also a recipient of Fulbright Scholarship, which he conducted research at Portland State University, OR, USA.

Besides, he served as the Dean, Director of Graduate School, and Department Chair positions in different universities.

His research interests include, but not limited to, management information systems, business analytics, leadership, organizational trust and fairness.

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Cem Ufuk Baytar is a researcher, an educator and a consultant specializing in management information systems, system analysis and design, e-commerce and data analytics. He earned his PhD in business administration from Beykent University, Istanbul. He has participated in various IT projects related to e-commerce, ERP, digital archiving and document management systems at both international and national levels. Currently, Cem Ufuk is a member of the Management Information Systems Department at Istanbul Topkapı University, Turkey.

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Hasan Temel completed his doctorate in 2025 at the Department of Management Information Systems, Graduate Education Institute, Istanbul Topkapı University. His dissertation examines the mediating role of digital literacy in the effect of talent management implemented in private schools on teachers' individual entrepreneurship and innovative behavior capacities. His academic work focuses on digital literacy, digital transformation, talent management, entrepreneurship and innovative behavior. A joint study derived from his dissertation will appear in the Springer book Sustainable and Resilient Supply Chains in the Generative AI Age.

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Mehmet Bilge Kağan Önaçan graduated from the Turkish Naval Academy in 1993. He received his first M.S. degree in Defence Technology (Computer Engineering) from Boğaziçi University in 2002 and his second M.S. degree in Management and Organization from Selçuk University in 2008. He earned his Ph.D. in Business Administration from Ankara University in 2015. He has served as a faculty member at the National Defence University and later worked at Simsoft, a company specializing in simulation technologies. He is currently an Assistant Professor in the Department of Information Systems and Technology at Istanbul Okan University. His research interests include Knowledge Management, Management Information Systems, and related fields.

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Zehra Antep received her bachelor's degree from Uludağ University in 2006 and her master's degree in Health Management from Beykent University in 2009. She subsequently earned her Ph.D. in Business Management from Beykent University in 2019. She has professional experience in hospital management and currently serves as an Assistant Professor in the Department of Management Information Systems at Istanbul Topkapi University. Her research interests include technology management, digital transformation, organizational change, and related fields.

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INTRODUCTION

How many people are sitting at the table today when a manager makes a decision? Who prepared the report in front of them? Which data, which model and which assumptions produced the recommendation on the screen? And if the decision turns out to be wrong, who will be held responsible?

A few years ago these questions might have sounded exaggerated. They no longer do. For a long time, the field of Management Information Systems rested on a simple but powerful assumption: the system processes data, and the human makes the decision. The information system was a tool in the manager's hands. It collected, organized and reported data and placed it in front of the decision maker, while judgment, interpretation and responsibility always stayed with people.

That distinction is becoming harder to maintain. Generative AI produces content. Digital twins build scenarios about the future. Algorithms buy advertising space within milliseconds, schedule employees' work and steer processes in public services. Systems no longer just present information; they make recommendations, generate outputs and, in some cases, take action. This shift is also not confined to one sector or one part of the organization. It reaches from knowledge management to innovation, from change management to public administration, and from advertising to data architectures.

The literature is following these developments closely, but mostly from the technical side. Most publications on prompt engineering come from computer science. Research on cybersecurity in cloud computing has grown exponentially over the past fifteen years. The digital twin literature concentrates on technical architectures and sector-specific applications. Meanwhile, several questions remain insufficiently answered. Through which mechanisms do technological capabilities turn into organizational value? How is the role of the human changing? How much can established management theories explain about this new situation? And how should the whole process be governed?

This book starts from precisely this gap. Its aim is to examine the transformation driven by AI and data-driven technologies from a Management Information Systems perspective, that is, from a view that treats technology, people and organizations together. The chapters contribute to this aim through different methods. Two chapters map their fields through bibliometric analysis. Three propose conceptual models or frameworks. One chapter draws on quantitative field research and another on qualitative field research, while the remaining chapters build the conceptual ground through comprehensive literature reviews.

Chapter 1, by Mehmet Bilge Kağan Önaçan, looks at prompt engineering from a knowledge management perspective. It offers a bibliometric analysis of 213 publications retrieved from the Scopus database. The findings show that the field is still largely in the hands of computer science, while publications in business and management remain limited. The chapter argues that prompt engineering should be positioned as a new competency within knowledge management and points to considerable research opportunities in ethics, practical applications and organizational integration.

Chapter 2, written by Cem Ufuk Baytar, traces the path from digital twin-based decision support to organizational value. Built on Design Science Research and Task–Technology Fit theory, the conceptual model identifies information quality, real-time visibility, predictive capability and simulation capability as core digital twin capabilities. It proposes a stepwise value-creation process in which these capabilities lead to decision quality through decision support capability, then to organizational agility and, ultimately, to organizational performance.

Chapter 3, by Çağla Özen, follows the shift from human–computer interaction to human–AI collaboration. Starting from foundational concepts such as usability, accessibility and user experience, the chapter discusses how the computer is moving from a passive tool to an intelligent interaction partner. Its central argument is that the future of intelligent MIS will depend not only on technological intelligence but on how well

human–AI collaboration is designed, governed and built into organizational work.

Chapter 4, by Emad Aliwa, offers a bibliometric analysis of cybersecurity complexity in cloud computing. Covering 1,583 publications from 2010 to 2026, the analysis shows annual output rising from 3 papers in 2010 to 358 in 2025. The themes move from basic cloud security to threat detection and privacy, and from there to advanced technologies such as AI, blockchain, edge computing and post-quantum cryptography. The conclusion is clear: as the cloud becomes integrated with new technologies, its security complexity will keep growing.

Chapter 5, written by Zehra Antep, asks how AI is affecting organizational change processes. Established approaches, including Lewin, Kotter, ADKAR, organizational development, organizational learning and dynamic capabilities, are assessed against the learnability, partial autonomy, opacity and scalability of AI. The chapter shows that mechanisms such as leadership, participation and trust remain valid, whereas assumptions of linear processes and one-off implementation fall short. The proposed Double-Loop AI Change Governance Model combines the redesign of task and decision architectures with monitoring of the AI system throughout its life cycle.

Chapter 6, by Emre Ömer Zehir, treats generative AI as a co-creator in innovation management. Drawing on a structured integrative literature review, the chapter shows that generative AI can contribute to many stages of the innovation process, from opportunity recognition to commercialization. AI is strongest in speed, knowledge synthesis and recombination, while framing the problem, interpreting the context, exercising ethical judgment and remaining accountable stay with people. The chapter conceptualizes this complementarity through the Human–GenAI Innovation Co-Creation Framework.

Chapter 7, written by Rana Özyurt Kaptanoğlu, examines how perceived functional and emotional value affect the propensity for technological innovativeness in technology-intensive products. Data collected from 604 graduate students who actively use smartphones show

that both dimensions of value have positive and significant effects on users' openness to innovation. The chapter's contribution is to show that technical superiority is not enough on its own, and that users also need to experience a technology as useful and meaningful.

Chapter 8, by K. Anıl Çam, explores the relationship between digitalization, bureaucracy and merit in public administration from the viewpoint of middle-level managers. A thematic analysis of semi-structured interviews with 12 public managers, covering 430 coding instances, shows that digitalization does not eliminate bureaucracy but reconfigures it. Merit, in turn, is increasingly associated with digital competence, though it cannot be reduced to it. The chapter brings these findings together in the five-layer ÇAM Digital Bureaucracy-Merit Analytical Framework.

Chapter 9, written by Nermin Yıldırım, treats programmatic advertising as a data-driven information system. It examines the ecosystem of DSPs, SSPs, DMPs and real-time bidding mechanisms alongside personalization and targeting strategies. The chapter argues that programmatic advertising is more than a marketing method. It is a sociotechnical decision system shaped by the interaction of data, algorithms, platforms and human actors, which is why data quality, transparency, accountability and information security matter as much as performance.

Chapter 10, by Hüseyin Can Barutcu, traces the evolution of big data architectures from traditional file systems and relational databases to data warehouses, data lakes and data lakehouses. It covers cloud-based platforms, distributed processing technologies such as Apache Spark and Kafka, and the integration of big data with business intelligence and AI. The chapter draws attention to the risk of data lakes turning into "data swamps" and identifies the management of data structures required by machine learning applications as an important area for future research.

Chapter 11, by Hasan Temel, offers a conceptual review of digital literacy from the perspective of digital transformation and technology and innovation management. The chapter traces how definitions of the

concept have expanded from technical skills toward cognitive, ethical and social dimensions, and it compares six digital literacy models that, despite their different names, share a common core of technical, cognitive and social-emotional dimensions. It also shows that research on teachers has focused largely on measuring levels of digital literacy. The chapter argues that the highest stage of digital literacy, in which creativity and innovation are encouraged, is the strongest bridge linking the concept to digital transformation and organizational innovation.

The chapters can be read in order, but we can also suggest three reading routes. Readers interested in knowledge, interaction and decision-making may begin with Chapters 1, 2 and 3. Those focusing on organizations, innovation and users will find a shared discussion in Chapters 5, 6, 7, 8 and 11. Readers interested in data infrastructure, security and data-driven systems can read Chapters 4, 9 and 10 together.

Whichever route is taken, the chapters meet at a common point. In information systems, AI is moving from tool to partner. This does not take the human out of the system, but it does redefine the human's role, competencies and responsibilities. In its simplest form, the perspective running through the book can be described as governed human–AI collaboration.

Chapter 1:

Prompt Engineering Literature from the Knowledge Management Perspective: A Bibliometric Analysis

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Abstract

Prompt engineering, which defines the framework of interaction with artificial intelligence (AI), is emerging as a new competency within knowledge management (KM) processes. The rapid increase in the use of AI in daily life makes the role of prompt engineering increasingly significant in KM, tacit-explicit knowledge transformation, decision support, and digital transformation processes. The aim of this study is to present the current state of the prompt engineering literature from a KM perspective and to identify gaps and future research directions in the field. In this context, a search was conducted in the Scopus database using the keywords "knowledge management" and "prompt engineering" and 213 publications were analyzed. The analysis examined such aspects as the concentration of publications across fields, their distribution by year, major trends, emerging themes, and similar aspects. The results indicate that the prompt engineering literature remains largely focused on computer science, while publications in the fields of business, management, and accounting are limited; moreover, they reveal significant opportunities for future research in areas such as ethics, practical applications, and organizational integration. This study is expected to provide a foundation for research on the use of prompt engineering in knowledge management and to serve as a basis for further studies in this domain.

Keywords: knowledge management, artificial intelligence, retrieval-augmented generation, VOSviewer, large language models

1. Introduction

Knowledge management (KM) plays a critical role in organizations' strategic decision-making processes and in gaining competitive advantage. With the acceleration of digitalization, KM processes have become increasingly complex, making the development of new competencies essential. In particular, the proliferation of big data, analytics, and artificial intelligence (AI)-supported systems has led to the emergence of diverse skills within KM. These developments enable the reshaping of knowledge-based decision processes and allow organizations to implement digital transformation strategies more effectively. Therefore, it is crucial to benefit effectively from these new developments both in KM processes—covering knowledge creation, knowledge storage, knowledge sharing, and knowledge usage—and in tacit-explicit knowledge conversion processes—covering socialization, externalization, combination, and internalization (Önaçan, 2015, pp. 269-271). In this context, the competencies emerging alongside new technologies have become key factors shaping the future of KM.

In recent years, a new technology that has come to the forefront is AI. The rapid development and wide use of AI have had clear effects on KM and knowledge conversion processes. In this development, prompt engineering has appeared as a new skill. It helps produce more accurate and context-based results from AI systems, which makes decision support and digital transformation stronger. Therefore, prompt engineering is not only a technical tool but also a strategic skill in the KM field, opening new paths for research and practice.

Since prompt engineering is a relatively new concept that defines the framework of interaction with AI, its impact on KM is becoming increasingly evident. In the literature, studies that directly address this interaction are limited. Therefore, systematically examining the role of prompt engineering in KM, tacit-explicit knowledge conversion, decision support, and digital transformation processes is an important need from

both academic and practical perspectives. This need (or gap) opens new research avenues for scholars interested in the subject. The motivation of this study is to highlight this need and to reveal the intersection points between KM and prompt engineering. The aim of this study is to present the current state of the prompt engineering literature from a KM perspective and to identify gaps and future research directions in the field. In the subsequent sections, the conceptual framework, methodology, findings and discussions are presented, and the study concludes with results and recommendations.

2. Conceptual Framework

In this section, the theoretical foundation of the study is established. For this purpose, topics such as knowledge management, artificial intelligence, the role of AI in knowledge management, prompt engineering, prompt design, and the contributions of prompt engineering to knowledge management are presented.

2.1. Knowledge Management

One of the most critical building blocks of the information age is the process of transforming raw data into strategic value. Today, the management of knowledge, recognized as a strategic power, is of great importance. The traditional understanding of KM, which emphasized the preservation and conscious transmission of knowledge across generations, has today been replaced by a modern KM approach that uses advanced information technologies to create, store, share, and use knowledge to generate organizational value, marking a transition into an era based on cloud computing, big data, and AI integration. In this context, KM is defined by Önaçan (2022, p. 136) as the processes involving employees, business processes, organizational structure, knowledge assets/content, and technology, which aim to achieve decision superiority, competitive advantage, and positive business outcomes by collecting, organizing, recording, and transforming into useful knowledge the registered or unregistered organizational data and personal knowledge and experience-based accumulations obtained from both internal and external sources of

the organization, while ensuring that the right people can access this knowledge at the right time, in the right way, and from anywhere.

2.1.1. Knowledge Management Processes

KM is not a static state; it is a cyclical and dynamic set of processes. Although KM processes have been addressed with minor variations in the literature, they generally consist of four stages: knowledge creation, knowledge storage, knowledge sharing, and knowledge usage. Knowledge creation is the transformation of data and information obtained from internal and external sources into new knowledge by combining them with existing experiences and values. Knowledge storage is the organization and preservation of knowledge in accordance with objectives for future use. Knowledge sharing is the formatting, transfer, and dissemination of created knowledge by making it accessible. Knowledge usage is the effective application of knowledge in activities such as strategy, decision-making, process improvement, and problem-solving (Önaçan, 2015, pp. 269-270).

2.1.2. SECI Model

In the literature, the SECI model, which has gained significant importance, has also been referred to as the "knowledge conversion process", "modes of knowledge creation", "forms of knowledge generation" or "tacit-explicit knowledge conversion process" and its name derives from the initials of socialization, externalization, combination, and internalization. The SECI model, developed by Nonaka and Takeuchi (1995), explains the conversion between tacit and explicit knowledge. Explicit knowledge can be coded and transferred, whereas tacit knowledge is based on individual experience and intuition. The model assumes that these two types of knowledge continuously convert into each other and spread in a spiral from the individual to the organization. This process is illustrated in Figure 1 and briefly explained below.

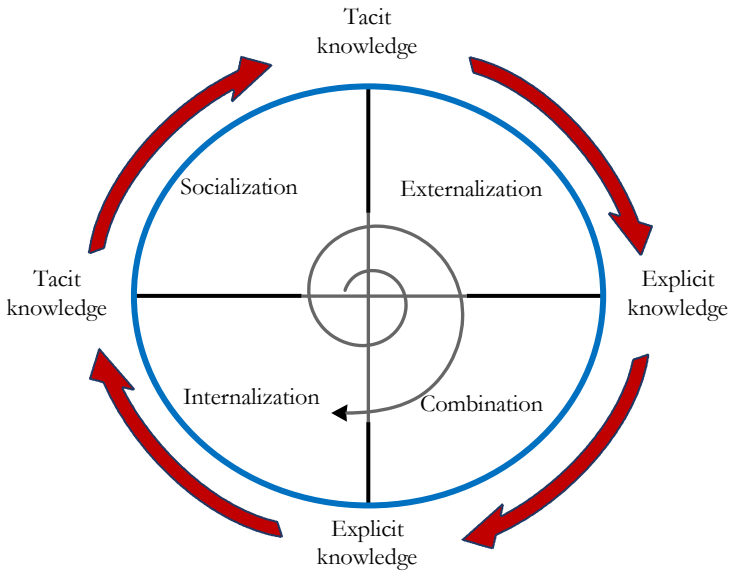


Figure 1. Tacit-explicit knowledge conversion process
Source: Adapted from Nonaka and Takeuchi (1995, p. 62)

Socialization refers to the conversion from tacit knowledge to tacit knowledge. Experience sharing and the master-apprentice relationship can be given as examples of this process. Externalization refers to the conversion from tacit knowledge to explicit knowledge. The articulation of ideas into reports, concepts, or guidelines can be given as examples of this process. Combination refers to the conversion from explicit knowledge to explicit knowledge. The synthesis of different reports and databases to create a new organizational document can be given as an example of this process. Internalization refers to the conversion from explicit knowledge to tacit knowledge. Employees reading organizational documents to develop their own mental practices and skills can be given as an example of this process. The continuous operation of this cycle is important for keeping organizational memory alive (Barreto & Abarca, 2025).

2.1.3. Benefits and Challenges of Knowledge Management

In a period when knowledge is recognized as a critical strategic resource, managing knowledge becomes inevitable. The management of knowledge provides significant benefits for organizations. Effective KM offers multidimensional benefits such as faster processes, reduced costs, increased employee motivation, the development of a learning culture, enhanced customer satisfaction, improved financial performance, and strengthened innovative capacity (Cantner et al., 2009; Figurska, 2014; North et al., 2004; Önaçan, 2015, pp. 20-21). In this respect, KM is considered one of the fundamental tools for achieving decision superiority and competitive advantage. However, KM is not an easy process and contains various challenges. Strategic misalignments, lack of qualified personnel, weak knowledge-sharing culture, organizational coordination problems, data and system errors, technological integration difficulties, security risks, and budget constraints are significant obstacles to this process (Kogi, 2025; Önaçan, 2015; Ramdani et al., 2026; Santhose & Lawrence, 2023). Therefore, while KM offers important opportunities to organizations, it is also a costly process that requires careful planning and strong support mechanisms.

2.1.4. The Role of Artificial Intelligence in Knowledge Management

AI, particularly through generative models and multimodal systems, creates a profound transformation in KM processes. Large language models (LLMs) (such as GPT-4, Claude, Gemini) and visual generation systems (such as DALL·E, Stable Diffusion, MidJourney) provide new opportunities in KM and knowledge conversion processes. Today, knowledge production is no longer solely human-centered but is increasingly shaped by hybrid processes involving human-machine interaction. This situation generates both significant opportunities and

new risks in terms of knowledge access, creation, accuracy, and organizational governance.

In the literature, the effects of AI on KM are discussed in terms of both benefits and risks (Aluçlu, 2024; Kayalı, 2026; Nakash & Bolisani, 2025; Yang, 2024; Zbuchea et al., 2019). The benefits include easier access to knowledge, more effective use of systematically documented knowledge, making tacit knowledge visible and shareable, accelerating knowledge sharing and collaboration, strengthening organizational learning and decision-making processes, transforming knowledge into a contextual and dynamic structure that increases organizational flexibility, achieving competitive advantage and agility, supporting a culture of continuous improvement, and introducing new contributions to the knowledge creation process through generative AI. On the other hand, risks such as the creation of false knowledge, cultural resistance, data privacy issues, excessive dependence on automation, difficulties in control, and epistemic uncertainty are noteworthy. Therefore, while AI is a powerful transformative actor in KM, it also necessitates the redesign of ethical and organizational control mechanisms.

2.2. Artificial Intelligence and Prompt Engineering

This section addresses AI, prompt engineering, and the ways in which prompt engineering contributes to KM.

2.2.1. Artificial Intelligence

AI is defined in various ways across different disciplines. According to McCarthy's classical definition, AI is the science and engineering of making intelligent machines, especially intelligent computer programs (Arslan, 2020, p. 76). According to the High-Level Expert Group on Artificial Intelligence (2019, p. 1), "AI refers to systems that display intelligent behavior by analyzing their environment and taking actions - with some degree of autonomy- to achieve specific goals".

The primary goal of AI is to develop machines capable of simulating complex functions unique to human intelligence, such as language processing, visual perception, problem-solving, learning, and decision-making. These systems mostly utilize machine learning methods to perform these functions, executing them in autonomous or semi-autonomous ways (Mutlu, 2024, p. 426). Its functional capabilities include perception, reasoning, learning, decision-making, and adaptation; while its technical capabilities encompass knowledge representation, problem-solving, learning algorithms, and generalization (Al-Khamees et al., 2026).

When examining the historical development, it is observed that the theoretical foundations were laid in the 1950s with Alan Turing's Computing Machinery and Intelligence article, and the field became an independent discipline with the 1956 Dartmouth Conference. In the 1970s-1980s, expert systems and symbolic AI came to the forefront; in the 1990s-2000s, machine learning gained importance with the rise of big data; and after 2010, deep learning based on multilayered artificial neural networks revolutionized fields such as natural language processing and computer vision. Today, generative AI (GenAI) is at the center of attention, while the future envisions the use of Artificial General Intelligence (AGI) (Lima, 2026).

GenAI refers to systems that learn patterns from large datasets and generate contextually appropriate outputs in response to user prompts. Built on deep learning and artificial neural networks, these models have the capacity to generate original content such as text, code, images, and audio. Their ability to produce coherent and contextual outputs based on learned patterns makes them transformative actors in KM processes (Feuerriegel et al., 2024, p. 111). AGI, which remains at the theoretical stage, refers to systems capable of learning and performing a wide range of tasks similar to human intelligence. While GenAI produces content from specific data types, AGI can generalize across contexts and has the potential to surpass human-level performance in diverse tasks. Although AGI, regarded in the literature as the ultimate goal of AI, has not yet been realized, large language models and multimodal systems are considered significant steps toward this direction (Bikkasani, 2025).

2.2.2. Machine Learning, Deep Learning and Artificial Neural Networks

Machine learning, deep learning, and artificial neural networks are complementary concepts. Machine learning enables inference from data, deep learning strengthens these inferences through multilayered algorithms, and artificial neural networks model this process with structures inspired by the human brain. To elaborate further, machine learning is an AI method that allows computers to learn from data without being explicitly programmed. The system extracts patterns from the provided data and generates predictions or decisions based on these patterns. It has subfields such as supervised, unsupervised, and reinforcement learning. This approach enhances the problem-solving capacity of AI while forming the foundation for more complex methods such as deep learning. Deep learning, a subset of machine learning, uses multilayered artificial neural networks to extract features from data. Compared to machine learning, it processes larger amounts of data in more complex ways, supporting the infrastructure of prompt engineering and LLMs (Akın & Şahin, 2024, p. 29). Artificial neural networks are mathematical models that form the basis of deep learning and are inspired by the functions of neurons in the human brain. Artificial neural networks consist of interconnected simple processing units. These units are likened to neurons in the human brain. The inputs to a neuron are first multiplied by the "weights" of the connections and then summed. The resulting sum is processed through an activation function. The activation function passes this value through a specific threshold to produce an "output". Thus, the network selects which information is important and transfers it to the next layer. Artificial neural networks process data in layers; each layer transforms the information further, ultimately producing a meaningful result (Öztürk & Şahin, 2018, pp. 27-33).

2.2.3. Large Language Models, Transformer Architecture and Natural Language Processing

Large Language Models (LLMs) are deep learning-based AI systems trained on datasets composed of extensive text corpora. LLMs are built on massive neural networks with billions of parameters and trained using vast text corpora. The learning process fundamentally relies on next-token prediction. The model, when given a context, determines the word (or token) most likely to follow by using statistical pattern recognition (Bender et al., 2021). These models learn the statistical patterns of language and perform tasks such as text generation, summarization, question answering, and information retrieval (Mienye et al., 2025). LLMs employ the transformer architecture for language modeling. The transformer uses the self-attention mechanism to establish relationships among all words in a sentence simultaneously, enabling the learning of long-range dependencies and parallel data processing. This technical infrastructure preserves context, enhances semantic accuracy, and allows LLMs to operate effectively in alignment with prompt engineering (Vaswani et al., 2017). LLMs utilize Natural Language Processing (NLP) methods to understand and generate human language. NLP is divided into two main components: Natural Language Understanding (NLU), which extracts meaning from text, and Natural Language Generation (NLG), which produces contextually appropriate responses (Jurafsky & Martin, 2026). By scaling these processes with large datasets and transformer architecture, LLMs provide a more powerful language processing capacity. This enables well-designed prompts to leverage NLU and NLG capabilities more efficiently, thereby enhancing the effectiveness of prompt engineering (Kumar, 2024).

AI uses LLMs and NLP techniques to understand human language. These LLMs process text primarily through tokenization and vector-based representation methods. In the tokenization process, text is divided into words or subunits, and each token is converted into numerical vectors that the model can learn from. AI interprets the context and meaning of text through these vectors; for example, attention mechanisms calculated based on the content of words and sentences establish relationships across

contexts. The attention mechanism enables the model to decide which tokens to focus on more, thereby concentrating on the most relevant information in the context. During this process, large datasets are used in model training, and token-based and vector-based representations are constructed on these datasets (Jurafsky & Martin, 2026; Vaswani et al., 2017). Additionally, prompts guide the model to provide specific information or answers within a given context. Through these representations, AI grasps the context and intent of the question and predicts an appropriate answer. By performing semantic similarity and meaning-level computations, it evaluates the alignment between actual and predicted answers (Reimers & Gurevych, 2019). Furthermore, threshold values and attention mechanisms enhance the contextual alignment, semantic coherence, and quality of the response to a question (Vaswani et al., 2017). Thus, AI can comprehend human language not only at a superficial level but also in terms of deeper meanings.

2.2.4. Issues Related to Artificial Intelligence

AI technologies provide significant contributions in many fields today, yet they also bring various risks. Ray (2026) categorizes these risks under hallucination, bias, privacy, security, ethics, and sustainability. Additionally, Seghid et al. (2026) highlight adversarial attacks, disinformation, socioeconomic inequalities, and environmental impacts; Pervez et al. (2026) emphasize transparency, accountability, and social impacts; while Mathews et al. (2026) underline intellectual property, legal responsibility, and regulatory gaps. These multidimensional issues necessitate the development of policies and regulations for the safe and responsible use of AI.

2.2.5. The Concept of Prompt Engineering

Interaction with AI systems occurs through prompting and prompt engineering (Schulhoff et al., 2025, p. 1). In general terms, prompt engineering refers to the process of designing, optimizing, and applying inputs (prompts) to obtain desired outputs from AI models (Şimşek, 2024). This discipline enables users to communicate effectively with AI

systems, thereby enhancing model performance and making it possible to achieve desired results (Tan et al., 2024). In other words, prompt engineering, in relation to context engineering, defines how communication with the model is established within the contextual knowledge space -specifically how inputs are expressed- and focuses on user-centered interaction design.

2.2.6. Problems Related to Prompts

Prompt design plays a critical role in ensuring the accuracy and reliability of outputs obtained from AI. The literature emphasizes that prompts can lead to various problems. Prompts written in natural language may contain ambiguity and polysemy, which increases the risk of producing incorrect outputs (Liu et al., 2023). Formal errors or missing context can result in inconsistent responses, while biases may reproduce and amplify social prejudices present in training data. In addition, malicious prompts can trigger the generation of harmful content (Fatawi et al., 2026). Excessively complex or lengthy prompts raise computational costs, leading to higher energy consumption and sustainability concerns. Therefore, prompt engineering is considered not only a technical process but also a research field that must be addressed from ethical and societal perspectives.

2.2.7. Prompt Design and Considerations

Prompt design refers to the systematic process of designing, optimizing, and applying inputs (prompts) to obtain desired outputs from AI models (Şimşek, 2024). This process is critical for obtaining reliable and goal-oriented responses from AI. The principle of "Garbage in, garbage out" meaning that the quality of inputs directly determines the quality of outputs, reflects the fundamental approach in this field (Şimşek, 2024; Sırvermez, 2024). Bsharat et al. (2023) emphasize that an effective prompt is not composed of random expressions but consists of five fundamental components brought together through a logical architecture:

Role: It is the artificial identity assigned to the model. For example, "Act as a senior KM expert" directs the model to generate responses from a specific expertise perspective.

Context: It defines the background of the task, the target audience, and environmental conditions. This makes the model's responses more accurate and relevant.

Task: It specifies exactly what is expected from the model. A clear and precise task definition ensures the model's focus.

Constraints: It establishes the boundaries, prohibitions, and rules of the response. For instance, "Use academic language, do not exceed 500 words" ensures the appropriateness of the output.

Output Format: It defines the structural form of the result. For example, "Provide the output in table format" ensures the model presents its response in a specific format.

Prompt type refers to the general category of interaction between the user and the model, while prompt technique denotes the specific methods used within these categories. In the literature, the most common types include new task prompts that do not require extensive training, reasoning and logic prompts, hallucination-reducing prompts, and code-generation prompts. Frequently used techniques within these types are zero-shot, few-shot, chain-of-thought, automatic chain-of-thought, self-consistency, ReAct, and tree of thoughts. These techniques play a critical role in making the outputs of prompt engineering more reliable, contextually appropriate, and efficient (Sırvermez, 2024; Tan et al., 2024). Properly structured prompts maximize the potential of AI models.

2.2.8. The Contribution of Prompt Engineering to Knowledge Management

The impact of AI on KM has been discussed above. Prompt engineering is also considered to have direct effects on KM. These can be listed as follows (Aljonied, 2026; Gibreel et al., 2026; Koutsiana et al., 2026; Wang et al., 2025): First, prompt engineering makes significant

contributions to knowledge creation. It enables more effective use of AI's NLP capacity; prompts determine the context and thereby generate accurate and goal-oriented knowledge. Role assignment ensures that content is tailored to decision-makers, and formats such as tables, bullet points, or risk matrices allow direct integration into decision support systems. Reliability is enhanced by adding references, dates, and criteria. Additionally, the generation of educational materials (e.g., quizzes, case analyses, role-playing) becomes possible. Advanced prompts can summarize and report large datasets, thereby generating new insights.

Secondly, prompt engineering facilitates knowledge sharing. Well-designed prompts enable users to obtain clearer and contextually appropriate results, producing outputs based on reliable sources. By adding criteria such as "from academic articles" or "post-2024 data", prompts can retrieve focused information; advanced prompts can condense hundreds of pages of data into concise summaries. Role assignment makes search results suitable for decision-makers, while the use of common terminology within an organization ensures knowledge standardization and consistency in communication.

Thirdly, prompt engineering makes knowledge storage organized and accessible. Through prompts, data can be generated in formats such as tables, JSON, or XML and stored in databases; metadata such as source, date, author, and topic can be automatically added to ensure organization. Tasks such as "separate by topic headings" systematize the storage process, large datasets are summarized for efficient space usage, and directives like "prepare for long-term archiving" support the archiving process.

Fourthly, prompt engineering makes the use of knowledge contextually appropriate, fast, and easily integrated into decision-support processes. Prompts ensure that outputs are tailored to the user; formats such as risk matrices, SWOT analyses, and scenario planning can be directly applied in decision-making processes. The same information can be transformed into reports, presentations, summaries, or educational

materials through different prompts. It also facilitates the generation of new analyses and insights from stored data.

Fifthly, it plays a critical role in the SECI model. Within socialization, prompt engineering facilitates the transfer of synthesized tacit knowledge acquired from different experts in AI to other individuals through well-designed prompts. It provides a common language and format, enables digital sharing, and enhances accessibility. Within externalization, it helps transform tacit knowledge into written form, organizes its transfer into a specific format, and enables its conversion into organizational knowledge. Within combination, information gathered from scattered sources can be transformed into coherent knowledge repositories through prompt engineering. For example, the prompt "Compare these three reports and present the common themes in a table" enables the synthesis of explicit knowledge. Within internalization, prompt engineering accelerates the transformation of explicit knowledge into tacit knowledge during the learning process. For instance, the prompt "Summarize this report as a training scenario and add application examples" helps employees develop their own mental practices from organizational documents.

3. Methodology

In this study, the literature was examined through bibliometric methods using the results of a search conducted in the Scopus database on June 29, 2026, with the keywords "knowledge management" and "prompt engineering" applied to titles, abstracts, and keywords. The following query was used in the search: TITLE-ABS-KEY("knowledge management") AND TITLE-ABS-KEY("prompt engineering"). Boolean operator "AND" was used to combine the keywords, and the search was restricted to the fields TITLE, ABSTRACT, and KEYWORDS. Additionally, a separate search was conducted with the query TITLE-ABS-KEY("knowledge management") AND TITLE-ABS-KEY("prompt engineering") AND TITLE-ABS-KEY("bibliometric") and no publications were found in Scopus. The search covered all years available in Scopus up to the aforementioned date. All records identified in the

search results were included in the study, except for two publications that did not have abstracts. Based on the purpose of the study, the research questions (RQs) were identified and presented with their respective RQ numbers (RQ#), along with the methods used to answer each RQ, in Table 1.

Table 1. Research questions (RQs)

RQ#	RQ	Method
RQ1	What is the distribution of publications by subject area?	DA (Scopus filters)
RQ2	What are the document types of the publications?	DA (Scopus filters)
RQ3	What is the distribution of publications by language?	DA (Scopus filters)
RQ4	What are the source types of the publications?	DA (Scopus filters)
RQ5	What is the open-access status of the publications?	DA (Scopus filters)
RQ6	What is the distribution of publications by country?	DA (Scopus filters)
RQ7	What is the level of Turkey's academic contribution in this field?	DA (Scopus filters)
RQ8	What is the distribution of publications by year?	DA (Scopus filters)
RQ9	What are the citation counts of the publications?	BA (VOSviewer; Citation, Documents)
RQ10	Which sources have the highest number of publications and citations?	BA (VOSviewer; Citation, Sources)
RQ11	What are the most frequently used keywords?	Co-occurrence Analysis (VOSviewer; Keywords) TA (Copilot, GEMINI)
RQ12	Which thematic areas stand out in the studies?	Text Analysis (VOSviewer; Title and Abstracts) TA (Copilot, GEMINI)

Different analytical techniques were applied in line with the research questions. RQ1-8 were examined through descriptive analysis (DA) using the filters of the Scopus database. The other research questions were subjected to bibliometric analysis (BA), co-occurrence analysis, and text analysis using VOSviewer. For RQ11 and RQ12, thematic analysis (TA) was conducted with the support of Copilot and GEMINI. The usability of GenAI in scientific research is nowadays widely acknowledged (Knöchel et al., 2025). During TA, terms in each category were first sub-categorized, then common axes among these categories were identified, theme names representing the clusters were created, and finally, the

clusters were interpreted. Support and suggestions for alternative perspectives was obtained for these processes from these mentioned AI tools. Finally, by the researcher, different suggestions and viewpoints were compared and evaluated, final decisions were made, and interpretations were provided.

Scopus, developed by Elsevier, is one of the largest abstract and citation databases, covering a wide range of publications in social sciences, business, engineering, and health sciences. Compared to other databases, it was chosen because it includes more journals and conference proceedings, provides up-to-date citation data, and is widely used in bibliometric analyses (Burnham, 2006).

After the dataset was created, VOSviewer software was used for certain analyses together with Scopus filters. Developed by Van Eck and Waltman (2010) and freely available, this software is a powerful tool for visualizing and clustering bibliometric networks. VOSviewer supports techniques such as citation analysis, co-authorship analysis, co-occurrence analysis, and keyword mapping. Thus, trends, relationships, and thematic areas in the literature can be presented more clearly.

As a methodology, BA is a systematic approach to revealing trends, patterns, and impacts in the scientific literature. It uncovers the structure of scientific studies by measuring and mapping data such as publications, citations, and keywords. Donthu et al. (2021) define this method as a powerful tool for evaluating the development of research fields with objective data and identifying future directions. In this study, BA was chosen not only to describe the current state but also because it is a strong method for revealing gaps in the literature and highlighting future research opportunities.

This methodological framework, while primarily based on the bibliometric analysis approach, enables the study to reveal both quantitative trends and qualitative thematic orientations. Thus, the current state of prompt engineering literature within the context of knowledge management is assessed in this study from a holistic perspective.

This study does not fall within the scope of research requiring ethics committee approval, such as those involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

4. Findings and Discussions

The findings obtained within the scope of the study, together with the related discussions, are presented below in a way that addresses the research questions.

4.1. Distribution of Publications by Subject Area

When examining the distribution of 213 publications obtained from the Scopus database by subject area (Figure 2), the largest share is found in the field of Computer Science (181 publications, ~41%). This is followed by Engineering with 69 publications, Mathematics with 46, and Decision Sciences with 35. Social Sciences (26), Medicine (13), Business, Management and Accounting (10), Materials Science (8), and Physics and Astronomy (8) are represented at a more limited level. In addition, a small number of publications are also found in Arts and Humanities and other fields. Some publications are listed in more than one subject area in Scopus. Because of this, the total counts exceed 213 publications.

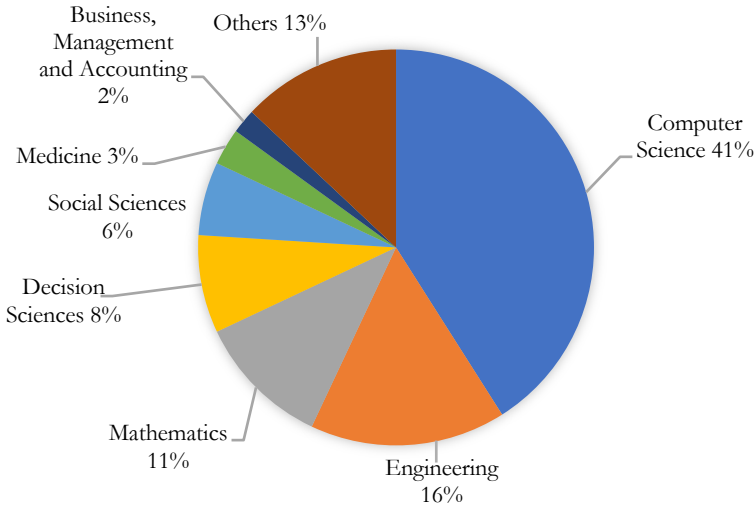


Figure 2. Distribution of publications by subject area

The findings indicate that, from the KM perspective, prompt engineering studies are largely concentrated in technical disciplines. The high proportion in computer science and engineering stems from the concept's direct association with AI systems and efforts to develop supporting infrastructures. This reveals that, at the outset, technical dimensions such as algorithm development, modeling, and system integration were prioritized. Publications in mathematics and decision sciences, on the other hand, reinforce the analytical dimension by focusing on criteria such as optimization, accuracy, and efficiency.

The low proportions in Social Sciences and Business, Management and Accounting indicate that prompt engineering has not yet been sufficiently examined in organizational contexts and KM processes. This gap offers new research opportunities, particularly in KM and knowledge conversion processes, decision support systems, and digital transformation.

The limited number of studies in fields such as medicine, materials science, and physics indicates that the concept has begun to be applied in different contexts. This diversity suggests that prompt engineering can be regarded not only as a technical tool but also as a method supporting KM

and knowledge conversion processes across different disciplines. However, the limited number of studies in these areas indicates that the field is still at an early stage and requires further research.

4.2. Document Types of the Publications

When examining the distribution of publications by document type (Figure 3), the largest share belongs to conference papers (151 publications; ~71%). This is followed by articles (50), books (5), book chapters (4), and reviews (3).

In the humanities, conferences function as testing grounds, journals provide scientific validation, and books offer synthesis and broader frameworks. In computer science, on the other hand, conference papers are often not merely preliminary steps but final peer-reviewed publications (CASRAI Editorial Board, 2026). Accordingly, when computer science and the humanities/social sciences are examined separately, publications in computer science consist of 141 conference papers, 31 articles, 4 books, 3 book chapters, and 2 reviews. In the humanities and social sciences (including 'Arts and Humanities', 'Social Sciences', 'Business, Management and Accounting', 'Economics, Econometrics and Finance', and Psychology), the publications comprise 27 conference papers, 7 articles, 3 book chapters, 2 books, and 1 review.

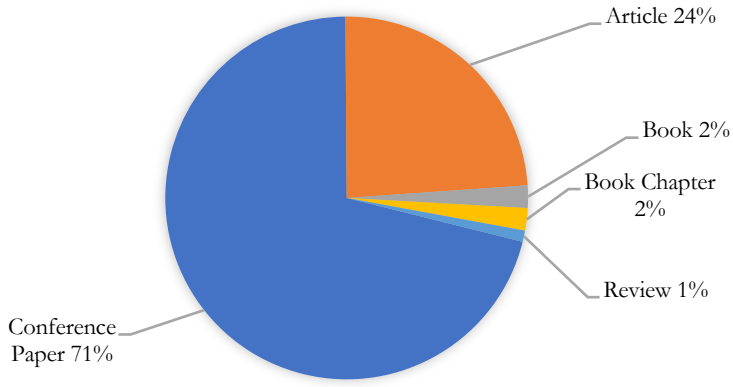


Figure 3. Distribution of publications according to document types

This distribution shows that the prompt engineering literature largely consists of conference-based outputs. Most publications are in the field of computer science and in the format of conference papers; this aligns with the fact that conferences in this field are regarded as final publications. In the humanities and social sciences, however, the number of publications is quite limited. The high proportion of conferences indicates that the concept has been rapidly discussed within academic communities, but has not yet sufficiently evolved into in-depth articles and books in the context of KM. This picture suggests that the theoretical framework of prompt engineering in the field of KM has not yet been fully established and is progressing mainly through applied examples. Overall, the development of the field in computer science progresses through product, technology, and skill development. This suggests that usable and mature outputs are produced first, and then other disciplines build theoretical and applied studies upon them. The scarcity of books and book chapters indicates the need for further work to develop the theoretical and methodological framework, while the limited number of review studies highlights the lack of systematic evaluations.

4.3. Distribution of Publications by Language

When examining the distribution of publications by language (Figure 4), 208 publications (98%) are in English, while only five are in Chinese. This distribution demonstrates that the literature is shaped almost entirely through English, with contributions in other languages remaining very limited.

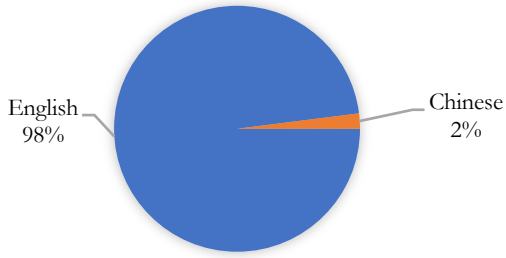


Figure 4. Distribution of publications by language

The language distribution reveals that prompt engineering is discussed globally in the context of KM primarily through English. The dominance of English demonstrates that studies on prompt engineering in KM reach international academic communities and possess global impact potential. However, the absence of publications in languages other than Chinese indicates that prompt engineering research in local KM contexts has not yet developed. This situation presents a significant opportunity for studies in Turkish and other regional languages. Research produced in local languages would better reflect the cultural and institutional differences of KM practices and reveal how the concept evolves in different contexts.

4.4. Source Types of the Publications

When examining the source types (Figure 5), the majority of publications consist of conference proceedings. Out of a total of 213 publications, 125 are conference proceedings, 60 are journals, 21 are book series, and seven are books. A book series is a multi-volume academic collection published at regular intervals on a specific theme or field, with volumes that complement each other.

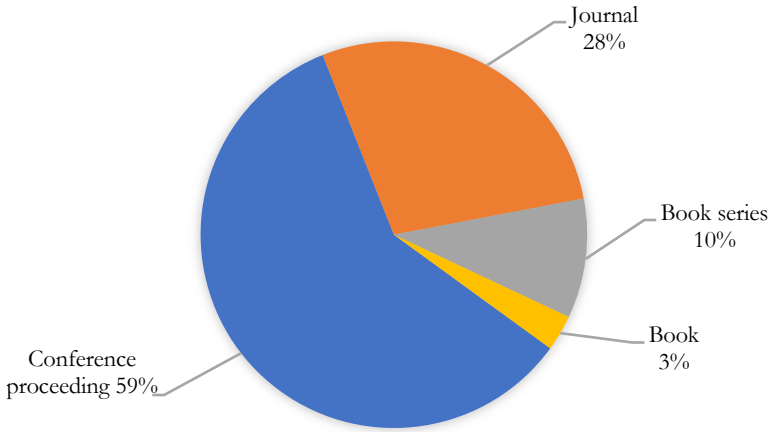


Figure 5. Source type of publications

This RQ is directly related to RQ2. In the answer to RQ2, conference papers, articles, books, book chapters, and reviews are generally published respectively in conference proceedings, journals, books, books, and journals. Therefore, the numbers of conference papers and conference proceedings would be expected to be close or even identical, but differences are observed here. This difference is considered to stem from the fact that some conference papers have been published in journals, books, or book series. The reason conference papers are published in journals, books, or book series may be that conference proceedings provide short-term visibility, whereas book series, books, or journals create a more lasting impact and are regarded as long-term reference sources.

4.5. Open-Access Status of the Publications

When the open-access status of the publications is examined, it becomes evident that Scopus records classify open access in a specific way: if a publication is assigned to any open-access model (Gold, Green, Hybrid Gold, or Bronze), it is also tagged as "All Open Access." Thus, the "All Open Access" category should be understood not as an independent model but as an overarching classification that includes the other types of open access. In some cases, a single publication is marked with more than one open-access model simultaneously. This explains why the sum of the subcategories is higher than the number reported under "All Open Access." As shown in Figure 6, among the publications with open-access information recorded in the database, 56 are Gold (54%), 33 are Green (32%), 9 are Hybrid Gold (8%), and 6 are Bronze (6%). The "All Open Access" category, representing publications with at least one open-access tag, contains 77 studies. In contrast, 136 publications have no open-access information entered into the database. This means that the majority of the publications (approximately 64%) lack open-access information.

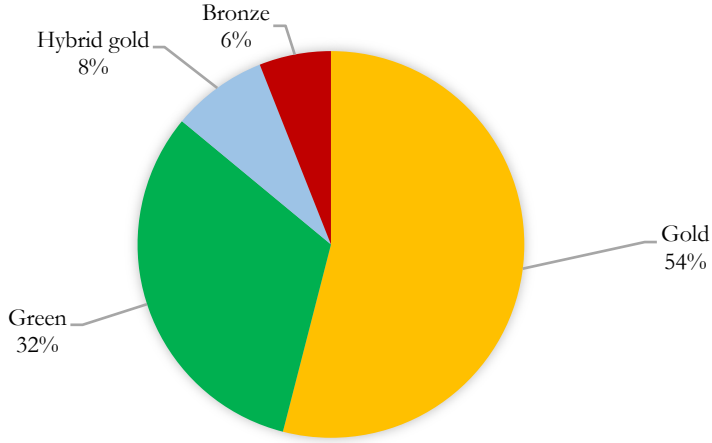


Figure 6. Open-access status of the publications

Gold open access makes publications available to everyone from the moment they are published and is usually supported by article processing charges (APCs) paid by the author or the institution. With a 54% share in the dataset, this model shows that it is accepted and becoming common in the literature. The Green model allows authors to share their work in institutional or subject-specific repositories; with a 32% share, it reflects a trend consistent with universities' open science policies. Hybrid Gold refers to publications in subscription-based journals that become open access through APC payments; its 8% share shows that it is less preferred. The Bronze model provides free access but does not specify reuse rights; with a 6% share, it is chosen at a lower level in the academic community. The "All Open Access" category is not an independent model but an overarching classification that includes Gold, Green, Hybrid, and Bronze types (open-access.network, 2025; Piwowar et al., 2018). Out of the 213 publications analyzed, 77 (36%) are in the All Open Access category. At the same time, 136 publications (64%) have no open access information recorded in the Scopus database. In Scopus, there is no specific data field indicating that a publication is not open access. A publication without open access information may either not be open access or may simply be a publication for which open access information has not yet been entered.

The UNESCO Recommendation on Open Science (UNESCO, 2021), the European Union's Horizon 2020 and Horizon Europe programs in which Turkey participates (OECD, 2025), TÜBİTAK's Open Science Policy (TÜBİTAK, 2019), and the National Artificial Intelligence Strategy (2021-2025) (T.C. Cumhurbaşkanlığı Dijital Dönüşüm Ofisi Başkanlığı [CBDDO] & T.C. Sanayi ve Teknoloji Bakanlığı [STB], 2021) together establish the legal and institutional framework that encourages researchers and institutions to publish in open access. Considering the binding provisions in these policy documents, it is expected—just as in other fields—that the literature on prompt engineering from a KM perspective will reach wider audiences and gain greater international visibility.

4.6. Distribution of Publications by Country

When examining the distribution by country (Figure 7), China holds the largest share with 87 publications (~35%). The United States follows with 32 publications, India with 18, Germany with 16, and Italy with 10. Countries with moderate contributions include Australia (8), the United Kingdom (7), France (5), Singapore (4), and Finland (4). Turkey, Switzerland, South Korea, and Greece each contribute 3 publications, representing ~1% of the total. Countries with lower contributions include Brazil, Ukraine, Taiwan, Spain, and Saudi Arabia (2 publications each), as well as Lebanon, Japan, Ireland, Denmark, Canada, and Bangladesh (1 publication each). The "Others" category covers 21 publications, accounting for ~8% of the total. It should be noted that some publications are affiliated with more than one country. As a result, the raw counts add up to more than the total number of publications. In addition, due to rounding, the sum of percentages may not equal 100.

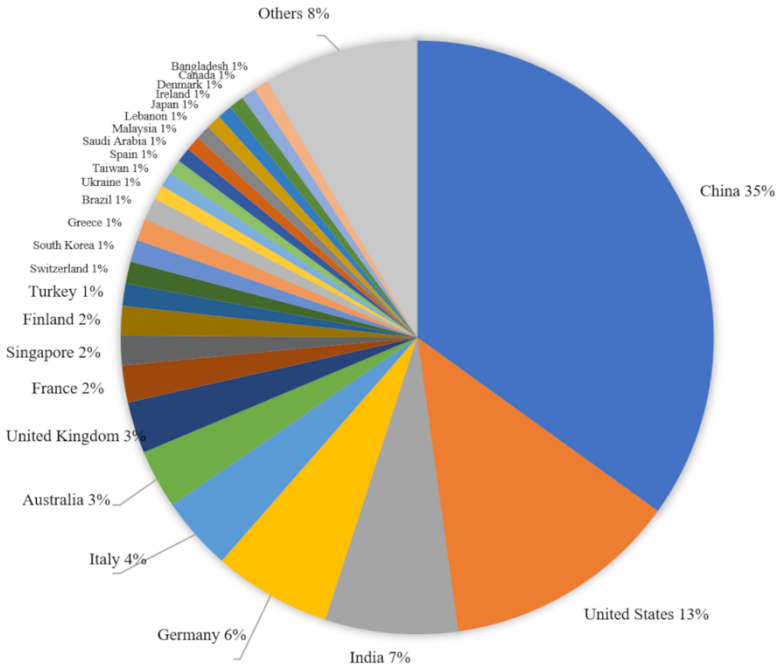


Figure 7. Distribution of publications by country

The country distribution indicates that, from a KM perspective, the prompt engineering literature is still concentrated in certain countries. This shows that while the field has begun to attract global interest, scientific output is not evenly distributed across countries. The fact that many countries are represented by only a small number of publications suggests that studies combining KM and prompt engineering are still in a developmental phase. It is anticipated that in the coming years, with the increase of research from diverse regions, both geographical diversity and the theoretical accumulation of KM perspectives in the literature will be strengthened.

4.7. Level of Turkey's Academic Contribution in This Field

From the perspective of KM, there are three studies on prompt engineering originating from Turkey. One of these is a journal article,

while the other two are conference papers. One conference paper was published in 2025, and the other two in 2026. All three publications are in English. Conference papers fall within the subject areas of computer science and decision sciences, while the article is classified as multidisciplinary.

Turkey's contribution to the prompt engineering literature remains limited. The small number of publications indicates that the field is still in its early stages, while the presence of studies across different types and disciplines demonstrates that the subject is not confined solely to its technical dimension. The growing interest in KM and AI (CBDDO & STB, 2021) may provide a foundation for strengthening academic contributions in the near future. In particular, the expansion of interdisciplinary research and the establishment of new programs and research centers at universities present significant opportunities to enhance Turkey's visibility in this field.

4.8. Distribution of Publications by Year

When examining the distribution of publications by year (Figure 8), it is observed that the first study in this field was conducted in 2023. In 2023, four publications were produced, followed by 20 in 2024. A remarkable increase occurred in 2025, with a total of 136 publications. In the first half of 2026, 53 publications were produced.

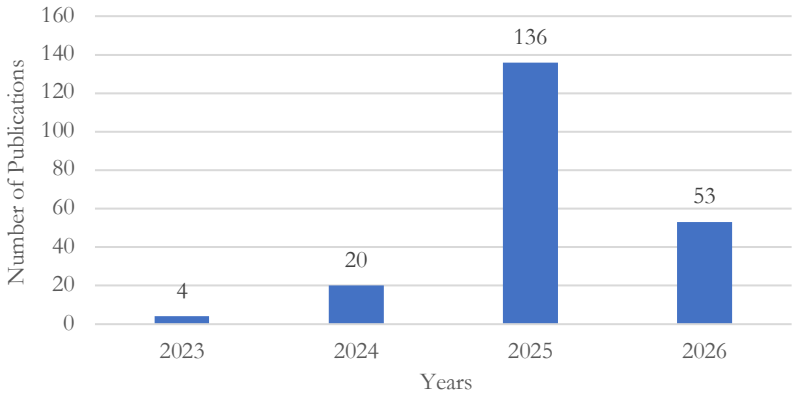


Figure 8. Distribution of publications by year

The data indicate that the field has rapidly attracted academic interest, with a significant increase observed in 2025. This surge suggests that the topic has been quickly accepted among researchers and studied intensively. Considering the upward trend in previous years, it is anticipated that the number of publications in 2026 may surpass that of 2025 by year's end. This trend demonstrates that the subject is becoming increasingly popular and gaining greater international visibility.

4.9. Citation Counts of the Publications

When "Type of Analysis" is set to Citation, "Unit of Analysis" to Documents, and the "Minimum number of citations of a document" to one in VOSviewer, the visualization in Figure 9 is obtained. The size of the circles is determined by the number of citations. The top 15 most cited publications are presented in Table 2. A total of 132 publications have not yet been cited.

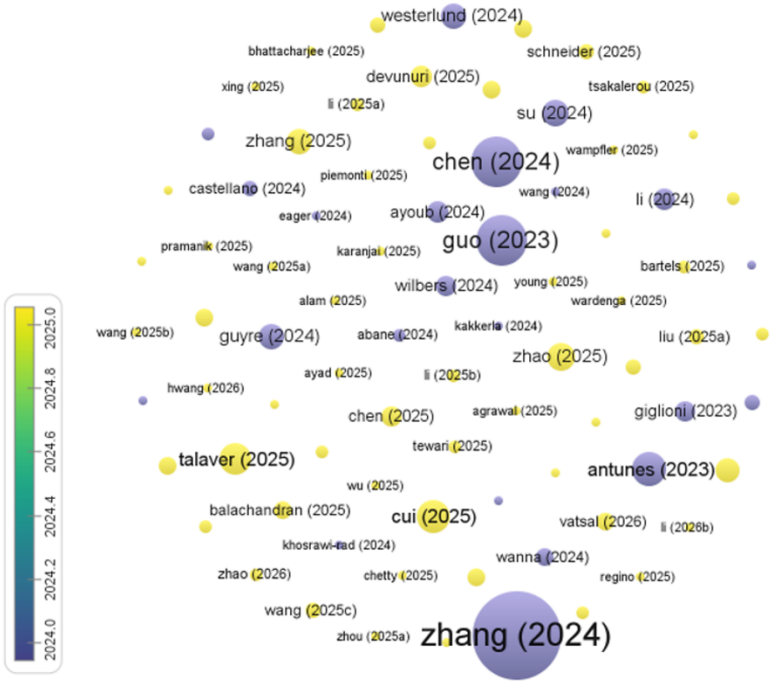


Figure 9. Citation counts of the publications

The citation distribution of studies published between 2023 and 2026 shows that, despite being a new field, it has rapidly gained visibility. Publications that received high citations in a short time have guided subsequent research through their methodological and conceptual contributions. The fact that studies published in 2025 and 2026 have not yet been cited can be considered normal for newly released works, reflecting that the field is still developing and its visibility process is ongoing. Therefore, monitoring which publications will stand out in the future is crucial for understanding research trends.

Table 2. The top 15 most cited publications

No.	Document	Citation Count
1	Zhang et al. (2024)	97
2	Chen et al. (2024)	32
3	Guo et al. (2023)	31
4	Antunes et al. (2023)	15
5	Cui et al. (2025)	14
6	Talaver and Vakaliuk (2024)	13
7	Zhao et al. (2025)	10
8	Su et al. (2024)	9
9	Zhang et al. (2025)	8
10	Guyre et al. (2024)	8
11	Westerlund and Shcherbakov (2024)	8
12	Du et al. (2025)	7
13	Devunuri and Lehe (2025)	6
14	Li et al. (2024)	6
15	Ayoub et al. (2024)	6

4.10. Sources That Have the Highest Number of Publications and Citations

In VOSviewer, when "Type of Analysis" is set to Citation, "Unit of Analysis" to Sources, "Counting method" to Full counting, "Minimum number of documents of a source" to one, and "Minimum number of citations of a source" to one, the visualization in Figure 10is obtained. The size of the circles is determined by the number of published documents. It is observed that the largest number of publications, nine in total, appeared in Ceur Workshop Proceedings, followed by five in

Communications in Computer and Information Sciences, three in Applied Sciences (Switzerland), and three in IEEE Access. It is observed that in the subsequent nine sources, each contains two publications.

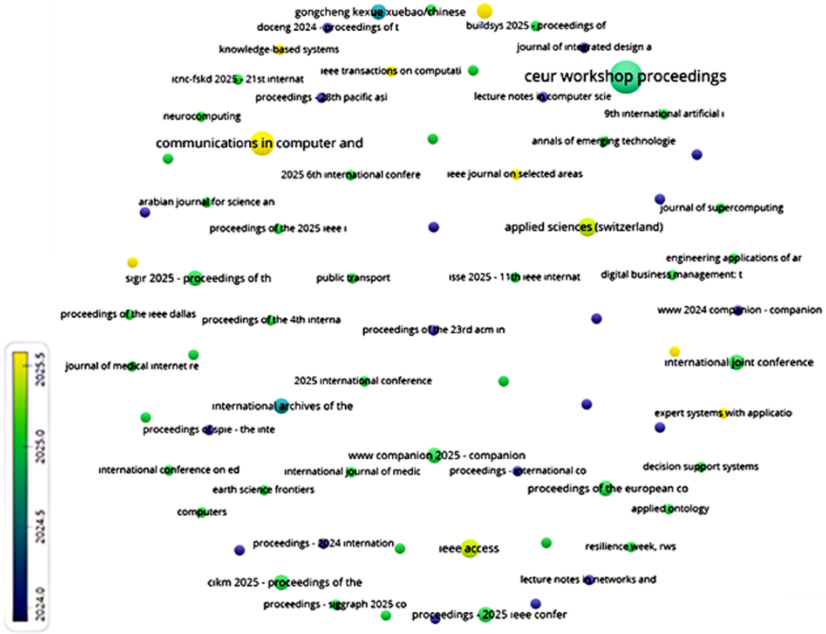


Figure 10. Journals with the highest number of publications

The top three sources with the highest citation counts are ranked as follows: Chemical Science with 97 citations, IEEE Robotics and Automation Letters with 32 citations, and Proceedings- 22nd IEEE International with 31 citations. The top 15 most cited sources, along with the number of published documents, are presented in Table 3.

Table 3. The top 15 most cited sources

No.	Source	Number of Documents	Citation Count
1	Chemical Science	1	97
2	IEEE Robotics and Automation Letters	1	32
3	Proceedings - 22nd IEEE International…	1	31
4	CEUR Workshop Proceedings	9	19
5	Proceedings of the 23rd ACM International…	1	15
6	SIGIR 2025 - Proceedings of the 48th International…	1	14
7	IEEE Transactions on Affective Computing	1	9

8	Proceedings - International Conference…	1	9
9	IEEE Access	3	8
10	Journal of Medical Internet Research	1	8
11	Lecture Notes in Networks and Systems	1	8
12	Proceedings of the 6th Conference on…	1	8
13	Neurocomputing	2	7
14	Gongcheng Kexue Xuebao / Chinese Journal…	2	6
15	Public Transport	1	6

When evaluated in terms of sources, it is observed that the studies are distributed across different publication platforms. This distribution suggests that the field has not yet consolidated around a few specific journals and that researchers from different disciplines are showing interest in the topic. On the other hand, the fact that the sources hosting the largest number of publications are not the same as those receiving the highest citations indicates that publication count alone is insufficient to explain scientific impact. In newly emerging research fields, conference papers play a crucial role as they enable the rapid dissemination of research findings. Conversely, the increasing publication of these studies in international peer-reviewed journals over time will contribute to the theoretical development of the field and enhance the academic visibility of prompt engineering literature from a KM perspective.

4.11. The Most Frequently Used Keywords

The co-occurrence analysis of author keywords examines the relationships between concepts used together in the same study and is widely employed as a bibliometric method to reveal the conceptual structure of a research field, its prominent themes, and the interconnections among these themes (Callon et al., 1983). Accordingly, a total of 697 author keywords obtained from 213 publications included in the analysis were subjected to structural examination using the VOSviewer software. In VOSviewer, "Type of Analysis" was set to Co-occurrence, "Unit of Analysis" to Author Keywords, and "Counting method" to Full counting. To reduce conceptual noise, eliminate marginal terms repeated only once or twice, and preserve current micro-trends in the field, after simulating different threshold values, "the minimum number of occurrences of a keyword" was set to three. The resulting data

visualization is presented in Figure 11. The distance between two concepts in the visualization approximately reflects their relative relatedness. In general, the closer two concepts are to each other, the stronger their relationship.

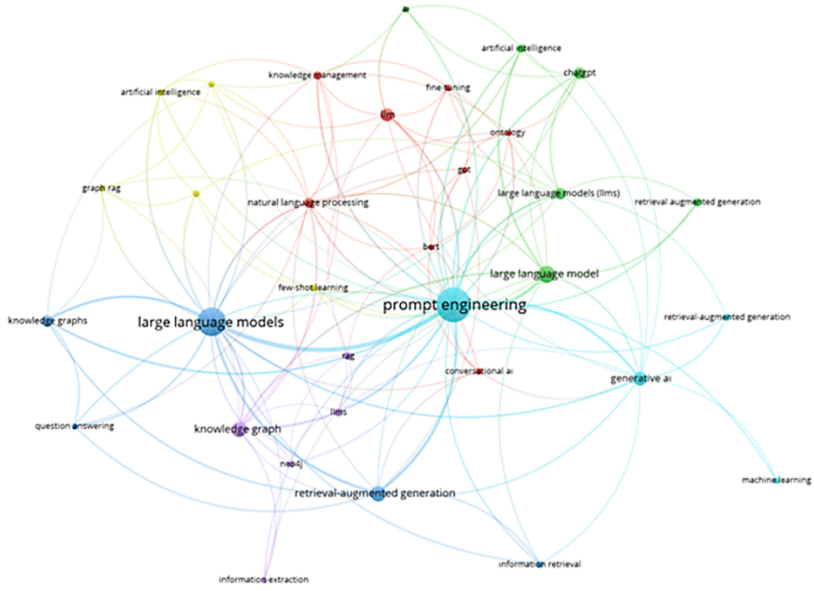


Figure 11. Most frequently used keywords

Among the 33 keywords that met the defined threshold, a total of 132 links and 306 total link strength were identified. The top 10 keywords ranked by occurrences, along with their Total Link Strength, are presented in Table 4.

Table 4. Occurrences and total link strength of keywords

No.	Keyword	Occurrences	Total Link Strength
1	Prompt engineering	92	146
2	Large language models	63	90
3	Large language model	23	33
4	Retrieval-augmented generation	18	36
5	Knowledge graph	18	30
6	Generative AI	13	27
7	LLM	11	14

8	Large language models (LLMs)	11	16
9	Knowledge graphs	10	22
10	ChatGPT	8	11

As a result of the clustering analysis, it has been observed that the literature is structured around six fundamental conceptual clusters that are interrelated yet differentiated in terms of their focal points. These clusters, which reflect the sub-disciplines and focal areas of the literature at the intersection of prompt engineering and KM, are summarized in Table 5 along with the themes they represent.

Table 5. Conceptual clusters formed within the keyword analysis

Cluster Number	Keywords	Represented Theme
Cluster 1	bert, conversational ai, fine-tuning, gpt, knowledge management, llm, natural language processing, ontology	Integration of KM and Language Model Architectures
Cluster 2	ai, artificial intelligence, chatgpt, large language model, large language models (llms), retrieval augmented generation	General AI Applications and Popular LLM Technologies
Cluster 3	information retrieval, knowledge graphs, large language models, question answering, retrieval-augmented generation	Information Retrieval and Intelligent Question-Answering Systems
Cluster 4	artificial intelligence, explainability, few-shot learning, graph rag, knowledge graph construction	Explainable AI and Graph-Based Knowledge Construction
Cluster 5	information extraction, knowledge graph, llms, Neo4j, rag	Information Extraction and Graph Database Architectures
Cluster 6	generative AI, machine learning, prompt engineering, retrieval-augmented generation (rag)	GenAI and Prompt Engineering Practices

When the constructed bibliometric network map is examined, it is observed that the two main focal points with the highest frequency are the concepts of LLMs and "prompt engineering". The central positioning of these two nodes indicates that a significant portion of the literature has been structured around this axis. However, when the clusters are analyzed, the repeated presence of "retrieval-augmented generation (RAG)" and

"knowledge graph" across multiple clusters reveals that these concepts function as bridges, supporting not only the technical infrastructure of the field but also its dimensions of accuracy and reliability. This situation, from another perspective, can be interpreted as a critical issue in KM related to prompt engineering, which involves preventing hallucinations and retrieving validated organizational knowledge. To briefly recall, RAG enables AI to access reliable external information, thereby reducing hallucinations, while the "knowledge graph" records information systematically like a ledger and verifies its accuracy. Therefore, other technical sub-concepts in the literature cluster around the central axis of LLMs and "prompt engineering", while simultaneously shaping the field's reliability and accuracy dimension through RAG and "knowledge graph". Moreover, when Occurrences and Total Link Strength (intensity of relationships with other keywords) are examined together, it becomes evident that the keywords "prompt engineering", LLMs, RAG, and "knowledge graph" not only appear frequently but also establish strong connections with other concepts, thereby shaping the structure of the field.

The analysis results demonstrate that the prompt engineering literature operates within a multi-layered structure, extending from information retrieval (information retrieval) to knowledge representation (ontology/knowledge graph), and from technical architectures (RAG, fine-tuning) to explainability (explainability). From the perspective of KM, it is evident that the literature is not confined to the question of "how to ask the model" but is directly integrated with the structuring of organizational knowledge (ontology, knowledge graph) and the reliable retrieval of this knowledge (RAG/graph RAG).

An examination of the keywords within the clusters reveals that synonymous expressions (LLM, LLMs, Large Language Model, etc.) appear across different clusters. The authors' free choice of synonymous terms without employing a thesaurus indicates that the field is still in the process of achieving terminological maturity and that different research traditions are contributing their own linguistic patterns to the literature. Although it would have been possible to standardize the keywords prior

to analysis by consolidating variations such as "LLM, LLMs, Large Language Model, Large Language Models (LLMs)" under a single heading, this study deliberately refrained from such standardization. The primary reason for this choice was to make visible the terminological diversity in the literature and to highlight how different research traditions label the same concept. This methodological preference provides an analytical contribution by demonstrating that the field has not yet achieved full terminological standardization. Therefore, the dispersion of the same concept across clusters in different forms is considered a significant finding that reflects both the developmental trajectory of the field and its interdisciplinary diversity.

In brief, Cluster 1, representing the theme of Integration of KM and Language Model Architectures, examines how language models such as GPT and BERT are adapted and fine-tuned within KM processes alongside ontologies. The primary focus is the integration of AI text-processing architectures with organizational knowledge infrastructures. Cluster 2, representing the theme of General AI Applications and Popular LLM Technologies, encompasses widely used tools such as ChatGPT and LLMs. It reflects the broad-scale, application-oriented, and popular dimensions of AI usage in the literature. Cluster 3, representing the theme of Information Access and Intelligent Question-Answer Systems, includes information access mechanisms supported by infographics and retrieval-augmented generation (RAG). The goal is to access accurate information and develop automated question-answer systems. Cluster 4, representing the theme of Explainable AI and Graph-Based Knowledge Construction, focuses on explainability (XAI), few-shot learning, and graph-based RAG applications. Transparency in KM, justification of decisions, and modeling information through graph structures are emphasized. Cluster 5, representing the theme of Information Extraction and Graph Database Architectures, covers information extraction from raw text, graph database technologies such as Neo4j, and RAG implementations. The technical focus lies in processing, modeling, and securely storing data. Cluster 6, representing the theme of GenAI and Prompt Engineering Practices, encompasses generative AI processes, machine learning, and

prompt engineering applications. Its central focus is on the practical aspects of prompt design and the optimization of generative processes.

4.12. Thematic Areas That Stand Out in the Studies

A map based on text data was created in VOSviewer using article titles and abstracts, and it is presented in Figure 12. Binary counting was selected when configuring the analysis settings in VOSviewer. "The minimum number of occurrences of a term" was set to six. To reduce semantic noise in the dataset and ensure conceptual purity, different threshold values for the minimum number of occurrences were simulated, and efforts were made to determine the most appropriate value. The critical point here is to exclude noise-generating words while preserving those that are meaningful for the analysis. The relevance score, which determines how thematically distinctive the selected terms are, was set at the default value of 60%. In this configuration, 110 terms, 5 clusters, 3,261 links, and a total link strength of 7,110 were identified.

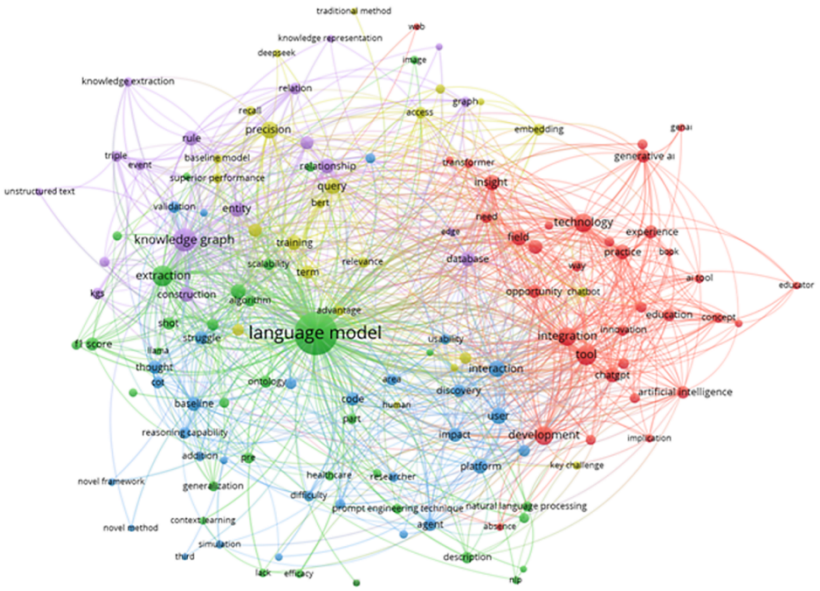


Figure 12. Heighted thematic areas

As a result of the co-occurrence analysis conducted with the VOSviewer text-mining tool, 110 terms in the prompt engineering literature from a KM perspective were grouped into five distinct clusters based on their mathematical density. The terms and themes contained in the resulting clusters are presented in Table 6.

Table 6. Themes that emerged within the scope of co-occurrence analysis

Cluster Number	Terms	Represented Theme
Cluster 1	alignment, baseline model, bert, complexity, construction, context learning, deepseek, domain knowledge, entity, experimental result, extraction, f1 score, generalization, hallucination, high quality, importance, kgs, knowledge distillation, knowledge extraction, knowledge graph, knowledge graph construction, knowledge representation, language model, llama, novel framework, ontology, part, pre, precision, query, recall, relation, robustness, rule, scalability, shot, shot learning, superior performance, term, training (43 terms)	Integration of Language Model Architecture with KM and Performance Reliability
Cluster 2	agent, ai tool, artificial intelligence, book, chatbot, chatgpt, creation, database, decision, development, education, educator, embedding, experience, factual accuracy, field, future research, gap, gemini, generative ai, healthcare, impact, industry, insight, integration, interaction, key challenge, knowledge management, natural language process, nlp, number, organization, platform, practice, prompt engineering tech, review, student, technology, tool, transparency, user, way (42 terms)	Socio-Technical Dimension and Organizational Adaptation
Cluster 3	addition, area, baseline, benchmark, chain, code, cot, difficulty, extensive experiment, http, novel, reasoning capability, researcher, significant improvement, struggle, thought, usability (17 terms)	Reasoning Capacity and Performance Testing
Cluster 4	graph, interpretability, lack, methodology, pipeline, relationship, structure (7 terms)	Graph Structures and Explainability
Cluster 5	Image (1 terms)	Visual Data and Visualization-Oriented Studies

The keyword clusters obtained through VOSviewer are considered as structures that reveal research focuses and thematic densities in the literature. In these clusters, concepts closely related to each other are

grouped together, showing which topics are addressed jointly, which areas exhibit concentration, and which research trends emerge. Thus, the keyword clusters reveal not only the frequency of terms but also their interrelations and shared themes. In this respect, interdisciplinary connections, methodological approaches, and application domains in the literature are mapped, offering researchers a holistic perspective. Consequently, the keyword clusters generated by VOSviewer function as an analytical framework for understanding the axes along which knowledge production in the examined field is concentrated and which themes dominate the literature.

In cluster analysis, the reason why some clusters contain a large number (e.g., 42-43) of words/concepts while others contain very few (or even only one) word/concepts is explained by the fact that the algorithm used by VOSviewer takes into account the density of connections between concepts, and particularly the "clustering resolution" parameter. Within this framework, concepts that establish strong connections are grouped into larger clusters, whereas those unable to form sufficient links are left independent or in smaller clusters (Sciaraffa et al., 2025). Below are comments regarding the themes represented in each cluster:

Cluster 1, representing the theme of the Integration of Language Model Architecture with KM and Performance Reliability, focuses on the development of LLMs (BERT, LLaMA, DeepSeek) and their integration into KM processes. Ontologies and knowledge graphs are employed for the representation of organizational knowledge, while terms such as precision, recall, and robustness highlight performance and reliability. Concepts such as hallucination and alignment indicate accuracy and quality issues in prompt engineering, whereas terms like context learning and shot learning pertain to enhancing the reasoning capacity of the model. Therefore, the cluster is structured around the axes of language model architecture, knowledge representation, and performance reliability.

Cluster 2, representing the theme of Socio-Technical Dimension and Organizational Adaptation, reflects the use of AI tools (ChatGPT,

GenAI, NLP) across diverse application domains (education, healthcare, industry, organizations) and their integration into KM processes. Terms such as knowledge management, integration, and database illustrate the adaptation of technologies to organizational knowledge infrastructures, while terms like factual accuracy, transparency, and impact emphasize reliability and ethical dimensions. Methodological expressions frequently appearing in abstracts, such as embedding, future research, and review, are considered reflections of the standard structural elements of academic summaries rather than indicators of thematic focus. Therefore, the cluster represents the socio-technical adaptation and organizational integration of AI and prompt engineering applications.

Cluster 3, representing the theme of Reasoning Capacity and Performance Testing, reflects research methods aimed at evaluating the reasoning ability and performance of LLMs. Terms such as benchmark and baseline reveal the comparative performance of models, while terms like extensive experiment and researcher indicate methodological expressions frequently appearing in abstracts. Terms such as Chain-of-Thought (CoT), reasoning capability, and thought emphasize the logical inference power and problem-solving capacity of the models. Terms like code, usability, and http highlight the technical implementation and practical dimension of these processes. Terms such as significant improvement, difficulty, and struggle reflect the challenges encountered and the progress achieved during the development of the models. Therefore, the cluster is structured around the axes of reasoning capacity, experimental validation, and performance testing.

Cluster 4, representing the theme of Graph Structures and Explainability, highlights the use of graph-based structures (graph, structure, relationship, pipeline) in the AI and prompt engineering literature, emphasizing the dimension of interpretability. Expressions such as methodology are considered to reflect the standard structural language of abstracts rather than the thematic orientation of the field. The term lack indicates limitations and areas requiring further development. Therefore, the cluster is structured around the axes of graph structures and

explainability, representing research trends focused on transparency and the recognition of limitations in the field.

Cluster 5, representing the theme of Visual Data and Visualization-Oriented Studies, is shaped around a single concept, "image". The use of visual data in the context of prompt engineering and KM, visualization techniques, and the integration of visual content constitute the core direction of this cluster. Its single-term composition indicates that this area represents a more marginal or independent research direction within the literature. Therefore, the cluster serves as a specific focal point highlighting the role of visual data in KM and AI applications.

5. Conclusion and Recommendations

In this study, conducted to reveal the current state of the prompt engineering literature from a KM perspective and to identify gaps and future research areas, data obtained from the Scopus database were subjected to bibliometric analysis. Findings related to the research questions defined in line with the study's purpose are summarized below.

The distribution by subject area reveals that, from a KM perspective, prompt engineering is strongly represented in technical disciplines, but there is a significant research gap in the context of KM and social sciences. This situation, as emphasized in the motivation of the study, indicates that research conducted from a KM perspective can provide original contributions to the literature.

The distribution of document types reveals that prompt engineering within the KM literature is still at an early stage and is predominantly shaped through conference papers. This finding indicates the need for more articles, reviews, and book studies in the future and highlights the necessity of strengthening the theoretical foundations of the concept within the KM context.

The distribution of languages demonstrates that prompt engineering in the KM literature progresses globally through English; however, research conducted in local languages is considered capable of providing original contributions to the field.

The distribution of source types indicates that, from a KM perspective, the prompt engineering literature is still predominantly shaped by conference proceedings; journal and book publications remain limited, yet such outputs are expected to increase over time, carrying the potential to strengthen the theoretical and methodological foundations of the field.

Findings on open access reveal that different access models are being utilized. Considering Turkey's national policy documents and the binding open access requirements in the European Union's Horizon 2020 and Horizon Europe programs, open access rates are expected to increase in the coming years.

The distribution across countries reveals that the literature has developed unevenly on a global scale. Countries such as China and the United States hold dominant positions in research production, while emerging academic ecosystems contribute only in a limited capacity. This situation points to both opportunities and areas of need for future research.

Although Turkey's contribution to prompt engineering from a KM perspective remains limited, national policies and growing academic interest suggest that this contribution will strengthen in the coming period. It is believed that Turkey's focus on research in this field will make a significant contribution to filling the gap in both national and international literature.

An examination of the distribution of publications over the years reveals that the field began with only a few pioneering studies in 2023, and there has been a remarkable increase in the number of publications over the years. This upward trend demonstrates that, from a KM perspective, the prompt engineering literature has rapidly attracted academic interest, become increasingly popular, and gained greater visibility.

An analysis of citation counts indicates that while some studies published between 2023 and 2026 quickly received high citations and shaped the field, others are considered to hold potential for impact in the future.

An examination of the sources from which the publications are made reveals that they are distributed across different platforms and are not yet concentrated around a few specific journals. The fact that the most published sources and the most cited sources are different indicates that publication count alone does not explain scientific impact. Although conference proceedings are important for rapid dissemination, future publications in international peer-reviewed journals will contribute to the theoretical development and visibility of the field.

The co-occurrence analysis shows that the most frequently used keywords are "large language models" and "prompt engineering", while other concepts cluster around these two centers to form six thematic groups. In particular, concepts such as LLMs and RAG emerge as critical nodes that connect different themes. The findings demonstrate that, from a KM perspective, the literature is multidimensional, terminologically diverse, and grounded in both practice and theory. These findings indicate that the prompt engineering literature is becoming an increasingly strategic research area in KM and will be further enriched through interdisciplinary interactions in the coming period.

The co-word and bibliometric network analysis conducted on the titles and abstracts of the studies reveals that five main thematic areas stand out in the examined literature. However, when the literature is considered as a whole, it is observed that the "prompt engineering from a KM perspective" body of work concentrates on two main axes: on one side, the technical/algorithmic infrastructure that transforms organizational data into knowledge graphs and ontologies; and on the other, the managerial/applied dimension that enables the adaptation of these technologies to organizational platforms, education, and professional practices. The other smaller clusters function as intermediary domains supporting these two main axes; reasoning capacity, explainability, and visual data-driven studies act as bridges between the technical and applied dimensions, thereby reinforcing interdisciplinary coherence.

When keyword-based clustering is evaluated together with clustering derived from word repetitions in titles and abstracts, it is observed that thematic concentrations in the literature display both similarities and differences. Keyword analysis primarily reflects the conceptual focuses used by researchers in classifying their articles, whereas abstract-based analysis reveals the content orientations and contextual relationships of the studies. Both analyses highlight language model architecture, knowledge management, and the socio-technical dimensions of AI applications; however, abstracts additionally emphasize more content-oriented themes such as reasoning capacity, explainability, and the use of visual data. This indicates that keywords point to general trends and popular concepts in the literature, while abstracts reflect the deeper content and methodological diversity of the research. Therefore, when both approaches are considered together, the conceptual framework and content richness of the field become visible in a holistic manner.

The findings of this study indicate that the prompt engineering literature, from a KM perspective, is still in a developmental stage. Future research should primarily focus on increasing methodological diversity and integrating approaches from different disciplines. Empirical studies that examine the role of prompt engineering in decision support systems, digital transformation strategies, KM processes, and tacit-explicit knowledge conversion processes will help fill existing gaps in the field. Moreover, the impact of cultural differences on KM processes, AI literacy, and ethical dimensions (such as data privacy, hallucination risks, and transparency) need to be addressed more comprehensively. In the context of organizational KM, applied research evaluating prompt libraries, training programs, and organizational adaptation processes (experiences in integrating AI and prompt engineering into KM infrastructure) will provide valuable contributions both academically and practically.

In the context of this study, no publications were found in the Scopus database when searching with the keywords "knowledge management", "prompt engineering" and "bibliometric". This finding highlights a significant gap in the literature and underscores the originality of the present research. Accordingly, the study can be considered one of

the first bibliometric contributions that explores the intersection between KM and prompt engineering, offering a unique perspective and paving the way for future investigations in this emerging field.

This study has certain limitations and assumptions. First, the analysis is based solely on the Scopus database, excluding publications from other databases. The study covers data up to June 29, 2026, and subsequent developments are not reflected. It is assumed that the data and filtering system provided by Scopus functioned correctly and that the analyses conducted with VOSviewer software were error-free. Additionally, it is assumed that the keywords used fully represent the literature. The study relies only on abstracts and bibliographic data, without full-text analysis; this may limit contextual diversity in thematic interpretations. Since terms may carry different meanings depending on context across articles, thematic interpretations are based only on shared patterns within clusters and may not capture the full contextual diversity of the literature. AI-based tools such as Copilot and Gemini were utilized in the thematic analysis. Thematic inferences are constrained by the algorithmic limitations and recommendation capacities of these tools. In conclusion, the findings are limited to the framework provided by the chosen database, software, and methods.

Declarations

Ethics Committee Approval: This study does not fall within the scope of research requiring ethics committee approval, such as those involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, AI tools such as Copilot and Gemini were utilized during the thematic analysis (TA) process—as explained in the chapter—and occasionally for language refinement. The author retains full responsibility for the content of the chapter.

Conflict of Interest: The author declares that there is no conflict of interest.

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Chapter 2:

Digital Twin Capabilities: From Decision Support to Organizational Value

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Abstract

Digital Twin (DT) technology offers an advanced information infrastructure capable of supporting decision-making processes by integrating digital representations of physical systems with real-time data, analytics, prediction, and simulation capabilities. However, the existing literature largely focuses on the technical architectures and sectoral applications of DT; the mechanisms by which technological capabilities are transformed into decision support capacity and organizational value are not sufficiently explained. This study develops a conceptual model to address this gap by examining digital twin-based decision support from a Management Information Systems (MIS) perspective. Design Science Research (DSR) provides the design logic for the model development process, while Task–Technology Fit (TTF) is used as the theoretical perspective explaining the fit between digital twin capabilities and the requirements of decision tasks. Based on an integrative synthesis of the literature, Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability are conceptualized as four analytically synthesized DT capability dimensions relevant to decision support. The proposed model suggests that these capabilities can support Decision Quality through Decision Support Capability, initiating a cascading value-creation process that extends through Organizational Agility to Organizational Performance. The study thus presents an integrated MIS framework in which organizational value emerges through a value-creation process that transforms technological capabilities into usable decision support aligned with decision-task requirements and subsequently into organizational outcomes.

Keywords: digital twin, decision support, management information systems, task-technology fit, design science research

1. Introduction

To accelerate digital transformation, businesses must collect the large volumes of heterogeneous data generated by physical systems, operations, and business processes and convert them into meaningful information for decision-making. In complex systems where real-time data flow is critical, information infrastructures that go beyond typical information systems' static reporting and monitoring functions are required. In this context, the Digital Twin (DT) has emerged as a technological method that maintains the data link between a physical thing, process, or system and its digital representation. While the breadth and application methods of the DT concept differ, the literature regards the connection between physical and digital aspects, data sharing, and modeling capability as fundamental qualities (Fuller et al., 2020; Tao et al., 2019; VanDerHorn & Mahadevan, 2021).

The evolution of the digital twin has expanded into diverse application areas, driven by advancements in technologies such as the Internet of Things (IoT), artificial intelligence, advanced analytics, and cyber-physical systems. These developments have broadened DT from a digital representation of a physical system into an infrastructure integrating real-time data use, modeling, analysis, prediction, and simulation (Dihan et al., 2024; Huang et al., 2021; Minerva et al., 2020). Accordingly, the organizational relevance of DT also derives from the potential to use the resulting information in operational and managerial processes.

One important consequence of this development is the growing research interest in the relationship between Digital Twin and Decision Support Systems (DSS). DT-based decision support approaches can combine up-to-date data from physical systems with analytical models, simulations, and predictive assessments, enabling decision-makers to evaluate current conditions and examine possible alternatives. For example, Zhou et al. (2021) combined digital twinning and analytics within a decision support system designed to support resilient port operations, while Meierhofer et al. (2021) examined the role of DT characteristics in developing decision support services in industrial ecosystems. From a

decision support perspective, these studies position DT as an infrastructure that integrates data provision with multiple information-processing and analytical functions.

Nevertheless, a substantial portion of the existing literature focuses on DT applications in specific sectors, their architectures, or their technical characteristics. Studies conducted in areas such as manufacturing, construction, healthcare, and urban systems have demonstrated that DT can be applied to a wide variety of problems (Caprari et al., 2022; Corral-Acero et al., 2020; Sacks et al., 2020). However, beyond this application literature, there is still a need for an integrative information systems perspective that explains which functions the different capabilities of the digital twin assume in the decision support process and through what mechanisms these functions are linked to organizational outcomes. In other words, while there is a significant amount of information in the literature regarding the question of How can the digital twin be implemented? the question of Which capabilities of the digital twin are transformed into decision support capabilities, and how do these capabilities support the organizational value creation process? requires a more holistic conceptualization.

This gap necessitates approaching the digital twin from an information systems (IS) perspective. According to the IS literature, the ability to create information, analyze it, and assist decision-making processes is a critical challenge for businesses dealing with uncertainty and complexity. Studies on analytical information processing capacities show that processing various data sources and transforming them into analytical outputs might help with decision-making processes (Naseer et al., 2021). Similarly, the literature on the application of artificial intelligence (AI) in business demonstrates that AI skills can be linked to many organizational activities such as information generation, process improvement, and decision support (Enholm et al., 2022). From this standpoint, the study conceptualizes the digital twin as an information systems capability through which diverse information-processing resources can be brought into decision-making processes. This conceptual perspective is developed

through a synthesis of the existing literature and does not represent an established classification.

The integration of AI and advanced analytics into DT broadens the reach of this information processing capability. Studies on the integration of AI into DT contexts show that machine learning and other artificial intelligence approaches can be utilized to predict, analyze, and model system behavior (Dai et al., 2025; Kreuzer et al., 2024). However, these technological advances do not guarantee higher-quality organizational decisions. Their decision-support value depends on how the information and analytical outputs generated by DT are incorporated into decision processes. The proposed model therefore incorporates decision support capability and decision quality as intermediary mechanisms between technology and organizational outcomes.

As a result, this study creates a conceptual model to describe the connection between digital twin capabilities and organizational outcomes. The model aims to explain how a digital twin's information and analytical capabilities, which are addressed under the headings of Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability, can be linked to decision quality via decision support capability, which can then be linked to organizational agility and, finally, to organizational performance. By combining the digital twin, DSS, and information systems literatures, the framework traces organizational value through the transformation of technological capabilities into decision-making processes.

2. Literature Review

2.1. The Conceptual Foundations of Digital Twin

Although the DT literature initially developed around the idea of representing a physical asset, process, or system in a digital environment, the scope of the concept has expanded considerably over time. Recent literature has expanded this view, describing DT as a structure that connects physical-system data with digital models for monitoring, analysis, and management (Barricelli et al., 2019; Fuller et al., 2020; VanDerHorn

& Mahadevan, 2021). Nevertheless, there is still no complete conceptual consensus in the literature regarding the definition, scope, and technical characteristics of DT. In their higher-level review synthesizing systematic literature reviews across different domains, Wooley et al. (2026) show that DT research varies considerably in terms of sectors, application purposes, and technologies employed. This diversity points to a multidimensional view of DT that integrates data, modeling, and system-integration elements.

The expanding scope of DT is also associated with the prominence of different technical and information-processing characteristics depending on the intended use. Barricelli et al. (2019) demonstrate that the concept has been approached differently across disciplines. Similarly, Boje et al. (2020) discuss the requirements for developing a semantic construction digital twin approach, while Sacks et al. (2020) relate the DT concept to construction information systems and emphasize the importance of integrating data and information sources. These studies indicate that the role of DT is not limited to representing a physical system in a digital environment; linking this representation with different information sources and systems broadens the scope of DT applications.

From this perspective, DT architectures depend on sustained data exchange and technical connections between physical systems and their digital representations. Minerva et al. (2020) examine DTs for IoT by reviewing technological specifications, sample projects, and architectural models; their perspective sees sensor connectivity within communication infrastructure and data processing components as critical components in the operation of such a technology architecture with a corresponding digital representation. Botín-Sanabria et al. (2022) provide a broader account of the evolution of DT technology throughout multiple application domains as well as a description of certain technical and application issues encountered. When this literature is considered holistically, it is possible to conclude that DT's data generation potential includes collecting raw data from physical systems and developing more context around these systems by associating incoming data with digital models and other information sources to develop meaning. The

information-infrastructure character of DT therefore encompasses both the technological connection between data collection and processing and the digital representation of physical-system states.

Recent studies reveal that as DT has become increasingly institutionalized across several industries, it has grown beyond its original application in engineering. Bae et al. (2025) conduct a thorough analysis of DT technology, applications, and challenges across several industries and sectors, demonstrating significant disparities in application approaches. Hasan and Crawford (2025) discuss the progression of digital twin technology from research-oriented development toward broader adoption in real-world business settings. These findings suggest that considering DT as a technical solution limited to a single sector may be overly restrictive. This stage is also where the conceptual interpretation used in this work from an information systems perspective comes into play: DT may be considered as a digital infrastructure that allows data acquired from physical systems to be used in various information-processing activities.

Another direction in the evolution of DT is the combination of digital representations with more complex analytical and cognitive processes. Bacnak et al. (2026) thoroughly investigate the Cognitive Digital Twin method and review studies aimed at broadening the DT concept to include cognitive skills. This development reflects a broader trend in DT research to build analytical and inferential capacities rather than just portraying the current state of a physical system. Adding cognitive or AI-enabled capabilities to DT does not, however, turn it into a decision-making system. Such advances may instead expand its capacity to generate information and analytical outputs for decision processes. Maintaining the conceptual separation between DT and decision support systems is thus critical.

For the purposes of this study, the significance of DT is precisely that distinction. DT is positioned not as an autonomous decision-making mechanism but as an information infrastructure that allows continuously updated data about a physical system to be linked with digital models and

used for monitoring, analysis, modeling, and, when appropriate, scenario evaluation. This positioning allows the study to examine the information and analytical inputs that DT can contribute to decision-making processes without associating its technical qualities with decision support capability. As a result, DT's increasing position as an information infrastructure serves as the foundation for the link between digital twins and decision support systems, which is explored in the next section.

2.2. Digital Twins and Decision Support

The importance of digital twins for decision support lies not simply in representing a physical system in a digital environment but in their ability to transform that representation into information that can be used in decision-making processes. Therefore, the relationship between DT and DSS should be considered within a broader framework than the technical integration of two technologies. From a decision support perspective, the central issue is how data obtained from physical systems are processed according to the requirements of a decision problem, how relevant information is selected, and how this information is transformed into outputs that enable decision-makers to evaluate alternatives. The view that information collection and processing activities in decision-intensive processes are interdependent with the decision itself also supports this relationship (Voorberg et al., 2021).

Applications reported in the literature show that DT can be incorporated into decision support processes at different levels. In urban facility management, manufacturing, energy, supply chains, and other complex systems, DT has been used to integrate data from physical systems, assess current conditions, and analyze possible intervention options (Bujari et al., 2021; Ghanbari & Nissinen, 2025; Li et al., 2024). A common feature of these studies is that across these applications, DT primarily functions as an information and analytical environment that provides a more comprehensive representation of the decision problem while leaving decision authority with the decision-maker. The role of DT in decision support should therefore be evaluated less in terms of its

individual technical components and more in terms of how these components connect to the decision-making process.

The scope of this relationship is expanding as analytical and learning-based methods are incorporated into DT architectures. Methods such as artificial intelligence, machine learning, optimization, and reinforcement learning can enable DT to move beyond reflecting the current state of a system and support decision-making by evaluating the potential consequences of different conditions or interventions (Mo et al., 2025; Orlova, 2025). Similarly, interconnected digital twins can contribute to shared situational awareness among different actors and support decision coordination (Schink et al., 2026). DT-based decision support can therefore extend beyond operational decisions concerning a single asset and provide greater capacity for coordination and evaluation in more complex and interconnected systems.

However, more data and more advanced analytical capabilities alone do not necessarily translate into higher-quality decision support. The ability of the decision-maker to identify what information is needed, understand the analytical results generated, and translate them into action is also crucial for the effectiveness of decision support. Studies on the importance of features such as interpretability, justifiability, and actionability in decision support show that it is not sufficient for analytical outputs to be merely technically correct (Coussement & Benoit, 2021). In this respect, the high-volume, real-time data generation capacity of decision support only creates value when this data is transformed into meaningful information relevant to the decision problem.

Nevertheless, the existing literature mostly examines the contribution of DT to decision support through specific applications or technological mechanisms. Some studies focus on data integration and real-time system visibility, while others concentrate on analytical mechanisms such as simulation, artificial intelligence, learning, or optimization. Although these studies reveal the contribution of DT to decision-making processes from different perspectives, there are a limited number of studies that explain, from a holistic information systems

perspective, the mechanisms through which the technological capabilities of DT are transformed into decision support capacity. The more important gap, therefore, concerns a systematic explanation of the capabilities and information-processing mechanisms through which DT generates decision support.

This study addresses the gap by framing the relationship between DT and DSS as a transformation process through which technological capabilities are translated into decision-support capabilities. The elements identified across these literature streams—data, visibility, analytics, prediction, and simulation—serve as empirical and conceptual inputs for the framework rather than as an established taxonomy of DT capabilities. Accordingly, the conceptualization of digital twin capabilities developed in the next section is positioned as a structure grounded in the existing literature but systematically organized in this study from a management information systems (MIS) perspective.

2.3. AI, Analytics, and the Expansion of Decision Support

The development of digital twins for decision support is increasingly associated with their integration with artificial intelligence, data analytics, simulation, and optimization techniques. However, incorporating AI into a digital twin architecture does not, in itself, imply an advanced decision support capability. What matters is the type of analytical outputs into which these technologies transform the data generated or integrated by the digital twin and how these outputs can be used in decision-making processes. Accordingly, AI and analytical techniques are treated as mechanisms that extend the information-processing and decision-support potential of DT rather than as defining components of DT itself.

The literature on information systems indicates that the organizational worth of artificial intelligence cannot be solely defined by its technological efficacy. Enholm et al. (2022) associate the establishment of commercial value through AI applications with not just technological

capabilities but also organizational processes and contextual usage. Applied to digital twins, this perspective shifts attention from predictive accuracy and technical functionality toward the conversion of DT-generated data into actionable insights for decision-making.

Studies on the integration of models, data, and AI, along with discussions on digital twins, also support this development. Wu et al. (2020) claim that when models, data, and artificial intelligence are combined for battery digital twins, this combination can jointly support analytical functions and intelligent management processes. He and Bai (2021) point out the importance of synchronizing data, modeling, simulation capability, and analytics in their investigation of digital twins in sustainable smart manufacturing. Within this setting, AI can extend the virtual representation by enabling more sophisticated analytical techniques in addition to automating analytical tasks.

A relevant distinction is that between predictive analytics and prescriptive decision support. Wissuchek and Zschech (2025) review prescriptive analytics systems from an information systems perspective, emphasizing the analytical processes involved in evaluating potential courses of action. This distinction is particularly relevant to digital twins. Predictive outputs indicate what may occur, whereas prescriptive analytics connects such outputs with the assessment of possible courses of action.

One application of this development is the integration of physics-based digital twins with simulation and optimization. Keshvarinia et al. (2025) demonstrate how a simulation-enhanced digital model can represent current system conditions while also providing a platform for evaluating alternative decision strategies through data-driven optimization. Similarly, Lian and Zhang (2025) integrate digital twins with a multi-criteria decision-making approach for a comprehensive assessment of many choice factors concurrently in the context of predictive maintenance. These applications illustrate how digital twin outputs can inform the evaluation of decision alternatives.

Integrating artificial intelligence into digital twins can extend their adaptive and learning capabilities. Mo et al. (2025) present a self-adaptive decision-making framework for industrial robots, whereas Orlova (2025) looks into reinforcement learning-based decision support within a digital twin management system. These studies demonstrate the integration of learning mechanisms with dynamic digital twin systems. These learning functions can inform decisions without necessarily transferring decision authority to the technology.

The literature suggests that artificial intelligence, analytics, simulation, and optimization can improve digital twins for use in decision-making processes. The common theme in these studies is that these technologies lack inherent decision support capabilities; instead, they permit the study of data generated by the digital twin, enable future predictions, and evaluate alternatives. The following section uses this distinction to clarify the theoretical positioning of the proposed framework.

2.4. Research Gap and Theoretical Positioning

A comprehensive review of the literature points to three key research gaps in explaining the relationship between digital twins and decision support systems. The first gap is conceptual. Despite the rapid expansion of the digital twin literature, there is no complete consensus on the definition, architecture, scope, and evolving functions of the concept. Wooley et al. (2026) reveal the conceptual and application-related diversity in digital twin research by comparing systematic reviews conducted in different sectors. Bacnak et al. (2026), on the other hand, consider the emergence of the cognitive digital twin approach as an indicator of the expanding scope of digital twins with more advanced analytical and cognitive functions. This situation necessitates clarifying not only "what a digital twin is" but also "what functions it can provide" in terms of organizational information and decision-making processes.

The second gap is mechanistic. As discussed in Section 2.2, studies across application domains have examined the use of digital twins for decision support. Li et al. (2024), Yin et al. (2025), Liang et al. (2025), and Keshvarinia et al. (2025) integrate digital twins with analytical, simulation, optimization, or decision-making approaches in different decision problems. However, these studies mostly focus on solving specific application problems. Therefore, the common mechanisms through which the technological capabilities provided by digital twins are transformed into decision support capacity have not yet been sufficiently explained within a comparable MIS framework across applications.

The third gap lies in the perspective of information systems and organizational values. While a significant portion of digital twin research develops along the axes of engineering, manufacturing, modeling, simulation, and technical architecture, the literature on decision support systems focuses on information use, analytical capabilities, decision tasks, and user requirements. Onwujekwe and Weistroffer (2025) demonstrate that decision support systems are increasingly integrated with artificial intelligence and machine learning (ML), and this development strengthens the trend toward intelligent decision support systems. However, a clear theoretical framework is needed to understand how this advanced decision support approach can be integrated with the continuously updated physical-digital representations of digital twins and how this integration affects organizational decision-making capacity.

The study responds to these gaps by conceptualizing the digital twin as an information infrastructure capable of extending the information-generation and information-processing capacity of decision support processes, while decision authority remains outside the technology itself. From this perspective, the central question is not whether a digital twin makes decisions but how the technological capabilities provided by a digital twin are transformed into decision support capabilities and through which mechanisms this transformation occurs.

Accordingly, the relationship between digital twins and decision support capability is conceptualized through the integrated effect of multiple functional dimensions derived from the literature. The full scope and conceptual justification of these dimensions are discussed in detail in Section 3. Thus, no predetermined taxonomy of DT capabilities is assumed at this stage; instead, the underlying problem to be addressed through the literature synthesis in the following section is established.

Theoretically, the study draws on two complementary perspectives. Design Science Research (DSR) makes it possible to approach the research problem as one of developing a conceptual solution by integrating knowledge and relationships that are dispersed across the existing literature. Task–Technology Fit (TTF), meanwhile, is used to explain the role of alignment between the technological capabilities provided by digital twins and the requirements of decision tasks in enabling these capabilities to create value in decision-making processes. In this way, the study moves away from the assumption that the mere presence of technology generates performance and develops a framework in which technological capabilities can be transformed into decision-support capabilities through their fit with decision-task requirements.

The study is conceptual in scope: it integrates relationships dispersed across the DT and decision-support literatures to develop a conceptual model and associated design knowledge, without undertaking empirical hypothesis testing or measurement-model development.

3. Theoretical Foundation and Conceptual Model Development

3.1. Theoretical Foundation: Design Science Research and Task–Technology Fit

The conceptual framework of this study complementarily utilizes DSR and TTF approaches to explain how digital twin-based decision support can be structured. DSR provides the design rationale for

developing a conceptual model for the problem identified in the literature, while TTF provides the theoretical perspective explaining under what conditions digital twin capabilities become meaningful for decision support. Therefore, the two approaches perform different but complementary functions in the model.

DSR provides an approach to information systems research that centers on the development of useful artifacts, models, or methods in response to identified problems (Hevner et al., 2004). Peffers et al. (2007) structure this process into six stages: problem identification and motivation, definition of the objectives for a solution, design and development, demonstration, evaluation, and communication. In this study, these stages are not applied as a complete empirical DSR process but are used as a design logic guiding the development of the conceptual model. At the problem identification stage, the fragmented treatment of the relationships among technological capabilities, decision support, and organizational outcomes in the digital twin literature is identified as the central problem. The objective of the solution is to develop an explanatory decision support framework that integrates these relationships. At the design and development stage, the literature synthesis is used to construct the following structure: Digital Twin Capabilities → Decision Support Capability → Decision Quality → Organizational Agility → Organizational Performance. The components of the model and the relationships among them are conceptually justified through comparison with the existing literature; however, the study does not claim to conduct an empirical demonstration or evaluation of the artifact. Accordingly, the demonstration and evaluation stages defined by Peffers et al. (2007) are considered beyond the scope of the present study and remain to be addressed through future empirical testing of the proposed model. The communication stage is addressed through the presentation of the conceptual model and its implications in this study.

The TTF perspective addresses a different issue within the model. According to Goodhue and Thompson (1995), technological characteristics alone are insufficient to explain the contribution of technology to performance; the fit between these characteristics and the

requirements of the task must also be considered. In this study, "task" refers to the information and analytical requirements of a decision task; "technology" refers to the technological and analytical capabilities provided by the digital twin; and "fit" refers to the extent to which these capabilities meet the requirements of the relevant decision task.

The study's conceptual structure explicitly highlights this alignment. Decision tasks requiring reliable and usable information are associated with information quality; tasks requiring a timely understanding of the current state of the system with real-time visibility; tasks requiring the assessment of future conditions with predictive capability; and tasks requiring the comparison of the potential consequences of alternative interventions with simulation capabilities. Fit therefore represents the degree of alignment between the requirements of a particular decision task and the relevant technological capability; it is not treated as a separate DT capability. Consequently, the same DT capability is not expected to provide the same level of decision support across different decision tasks.

Task–technology fit and decision support capability do not represent the same conceptual construct. Fit explains the alignment between the requirements of a decision task and the technological capabilities of the digital twin. Decision Support Capability, by contrast, is conceptualized in the literature synthesis of this study as a higher-order mechanism that explains how these technological capabilities can be used to support decision functions such as understanding the current situation, assessing predictions, and comparing alternatives. Thus, the role of TTF in this study is not to derive decision support capability directly as a component of the theory but to explain why the transition from digital twin capabilities to decision support capability depends on task–technology alignment.

DSR and TTF are therefore employed together, but at different analytical levels. DSR provides the design logic underlying the development of the proposed conceptual model, whereas TTF contributes to the theoretical explanation of the Digital Twin Capabilities → Decision Support Capability relationship within the model. The

resulting framework therefore specifies a gradual value-creation mechanism beginning with task-aligned technological capabilities and extending through decision support to organizational outcomes.

3.2. Digital Twin Capabilities: Information Quality, Real-Time Visibility, Predictive and Simulation Capabilities

The decision-support value of digital twins extends beyond the digital representation of physical systems. Their significance lies in the ability of this representation to bring together different data and model sources and create an information and analytical environment that can be used in decision-making processes. However, there is no single, widely accepted dimensional structure of digital twin capabilities in the literature. Therefore, in this study, information quality, real-time visibility, predictive capability, and simulation capability are used as an analytical synthesis of DT characteristics that have been addressed in different ways in the literature, viewed from a decision support perspective. These dimensions represent analytical components of the proposed conceptual model and are not intended as a standardized classification of DT capabilities.

Information Quality. The first dimension relates to integrating data from different sources to create a usable information base for decision-making processes. Malaibari et al. (2024) address the digital twin from a data management perspective, emphasizing the importance of data collection, integration, and management in DT structures. Ouedraogo et al. (2025) relate DT data management to the processes of data collection, processing, storage, integration, and sharing, while Alcaraz et al. (2025) focus on secure data sharing between different digital twin communities. Based on these findings, information quality is considered in this study as an analytical dimension representing the ability to transform data in the DT environment into usable and meaningful information for decision-making purposes.

Real-Time Visibility. The second dimension is the ability to monitor the current state of the physical system in real-time. Alonso et al. (2024) demonstrate that integrating IoT, big data, and other data sources with digital twin architecture can improve the flow of information between physical and digital environments. From a broader perspective, Yang et al. (2026) argue that digital twins are evolving into decision infrastructures that support continuous data exchange between physical and digital environments. In this context, real-time visibility combines high-frequency data generation with the decision-maker's ability to obtain an up-to-date view of system conditions at the time a decision is made.

Predictive Capability. The third dimension concerns the ability to generate predictions about future conditions based on the current state of the system. Weingram et al. (2025) examine the integration of digital twins with machine learning and scientific applications, demonstrating how DTs are expanding through data-driven learning and modeling functions. Abbasgholizadeh Rahimi et al. (2025), meanwhile, examine an AI-enabled digital twin approach in the context of clinical decision-making and show how AI-supported DT structures can be integrated with predictive and decision-making processes. In this study, artificial intelligence is not treated as an independent DT capability but as an analytical mechanism that can enable prediction. Predictive capability, therefore, refers to the ability to generate predictions about future system states or possible outcomes.

Simulation Capability. The fourth dimension refers to the ability to examine alternative conditions and interventions in a digital environment before they are implemented in the physical system. Madni et al. (2019) show that digital twins can enable the modeling of physical system behavior and the examination of different conditions within a model-based systems engineering context. Rasheed et al. (2020) emphasize the importance of modeling for analyzing system behavior, while Walton et al. (2024) associate a DT approach that integrates virtual, physical, and prescriptive analytical components with adaptive real-time decision-making. Similarly, dos Santos et al. (2022) systematically examine the use of discrete-event and agent-based simulation approaches for decision

support in the digital twin context, highlighting the role of simulation in evaluating alternative system behavior s. Within this framework, simulation capability is defined as the capacity to evaluate the potential consequences of alternative conditions or interventions in a digital environment before their physical implementation.

These four dimensions represent complementary technological capabilities that can be associated with different decision-task requirements from a TTF perspective. Decision tasks requiring reliable and usable information are associated with information quality; those requiring a timely understanding of the current situation with real-time visibility; those requiring the assessment of future conditions with predictive capability; and those requiring the comparison of the consequences of alternative interventions with simulation capabilities. Here, fit refers to the extent to which the relevant DT capability can meet the information and analytical requirements of a particular decision task. From a TTF perspective, these capabilities become relevant to decision support when they are meaningfully aligned with the information and analytical requirements of the decision task. This transformation is addressed in the following section through the concept of decision support capability.

3.3. Decision Support Capability

To explain the contribution of digital twins to decision-making processes, it is necessary to conceptually distinguish between the technical and analytical capabilities of a digital twin and the use of these capabilities in decision-making problems. Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability can provide important information and analytical resources for decision-making; however, the presence of these capabilities alone does not mean that decision support has been achieved. As discussed in the preceding sections from a TTF perspective, the value of technological capabilities for decision support depends on their fit with the information and analytical requirements of the decision task. In this study, Decision Support Capability is conceptualized as an integrative mechanism through which DT-based

information and analytical resources become usable for specific decision tasks; it is conceptually distinct from task–technology fit itself.

The fundamental challenge for decision support systems is to transform data and analytical outputs into insights relevant to the decision-maker. Phillips-Wren et al. (2021) discuss the role of data and analytics in generating more profound insights and decision support by integrating the relationships between business intelligence, analytics, and decision support systems. In the DT context, this places emphasis on the usability of operational data and analytical outputs for specific decision problems.

This transformation is primarily important for assessing the current situation and understanding the decision problem. The digital twin's ability to integrate different data sources and make the system state visible can contribute to a more comprehensive assessment of the decision-making environment by the decision-maker. West et al. (2021) demonstrate the potential of digital twins to support decision-making processes, while Gálvez del Postigo Gallego et al. (2025) systematically examine decision support within digital twins. In this respect, DT capabilities can support the necessary knowledge base for understanding the current conditions of the decision problem.

Another function of decision support is the evaluation of alternatives. Decision-makers must be able to assess alternative courses of action and their potential consequences in addition to understanding the current system state. At this point, the modeling and simulation capabilities of DT become relevant to decision support. Carlin et al. (2024) propose an interactive framework that incorporates decision-making requirements into digital twin design, while Mayer et al. (2025) approach the selection of different DT applications as a decision problem involving value and effort criteria. These studies support the importance of relating technological capabilities to decision requirements.

Similarly, predictive and analytical outputs can be used at more advanced stages of the decision-making process. However, generating a prediction about the future and using that prediction to evaluate possible actions do not represent the same functions. Monek and Fischer (2025)

propose the Expert Twin approach, in which a fuzzy-based decision-making module is integrated into a digital twin, while Walton et al. (2024) develop a DT approach that integrates physical and virtual components with prescriptive analytical elements to support adaptive, real-time decision-making. These examples demonstrate how analytical outputs generated by DT can be integrated with the evaluation of alternatives and action-oriented decision support.

Decision Support Capability is therefore conceptualized as a higher-order mechanism rather than as either a single DT characteristic or an established multidimensional scale. This conceptualization also distinguishes decision support from autonomous decision-making. The model retains decision authority with the decision-maker and focuses on technology's role in strengthening information processing and alternative evaluation.

Accordingly, the Digital Twin Capabilities → Decision Support Capability transition is a conceptual relationship derived from this literature synthesis rather than a causal relationship specified directly by TTF. TTF provides the theoretical rationale for this transition through the fit between technological capabilities and the requirements of the decision task. "Decision Support Capability," distinct from this fit, refers to the extent to which appropriate DT capabilities can be put to use in decision activities. In this way, the model moves from the question of "what capabilities does a digital twin possess?" to the question of "how are these capabilities transformed into usable decision support for specific decision tasks?"

3.4. Decision Quality and Organizational Agility

To explain the transformation of digital twin-based decision support into organizational value, it is necessary to consider the intermediary mechanisms between technological capabilities and organizational outcomes. This transformation is examined through the relationships among decision support capability, decision quality, and organizational agility. The model locates the organizational value of DT in

the use of information and analytical capabilities within decision processes, potentially improving decision quality and organizational responsiveness.

In this chain, Decision Support Capability represents an intermediate mechanism through which task-aligned digital twin capabilities can become usable in decision-making processes and potentially contribute to decision quality. In the DSS literature, decision quality extends beyond the quality of system-generated information to include the decision-maker's evaluation and use of that information in the relevant task. Indeed, Davern et al. (2008) show that human decisions can be susceptible to systematic errors and biases and that decision support can play a role in identifying and improving these problems in the decision-making process. Similarly, Raghunathan (1999) reveals that an increase in information quality does not automatically improve decision quality in every case; this relationship can vary depending on the decision-maker's qualifications. This distinction is important for digital twin-based decision support because large volumes of data, real-time visibility, or advanced analytical outputs do not, by themselves, imply high-quality decisions. In this study, Decision Quality is conceptualized as a construct reflecting the quality of the decision resulting from the evaluation of information relevant to the decision problem and the comparison of appropriate alternatives. Walton et al. (2024) show that a digital twin approach integrating physical and virtual components with prescriptive analytical elements can support adaptive real-time decision-making. The contribution of DT's analytical capacity to decision quality therefore depends on both the technical quality of its outputs and their relevance to the decision problem, possible actions, and subsequent decision process.

Organizational agility provides the next organizational-level link in this value-creation mechanism. In the information systems literature, Lu and Ramamurthy (2011) associate organizational agility with an organization's capacity to capitalize on opportunities and adapt its operations in response to changing conditions and identify positive relationships between IT capability and organizational agility. From this perspective, organizational agility emerges through the effective

deployment of technological resources within organizational processes rather than from technology use alone.

More recent literature on digitalization also supports this relationship. Ciampi et al. (2022) systematically review the literature on digitalization and organizational agility, showing that the relationships between IT (Information Technology) capabilities and big data analytics capabilities, on the one hand, and organizational agility, on the other, constitute an important area of research. This finding similarly cautions against treating digital twin capabilities as technological characteristics that directly generate organizational agility.

The proposed conceptual model advances a relationship between decision quality and organizational agility for future empirical examination. Accordingly, the Decision Quality → Organizational Agility link is advanced here as a conceptual proposition derived from the literature synthesis rather than as a previously established empirical relationship: when DT capabilities are used in alignment with the requirements of decision tasks, they can support decision-making capability; this capability can help decision-makers evaluate current conditions and alternatives more effectively; and decisions based on more relevant and up-to-date information may, in turn, support the organization's capacity to respond appropriately and in a timely manner to changing conditions. Organizational agility thus occupies a higher organizational level in the model and may emerge through improvements in decision support and decision quality.

This interpretation also recognizes the importance of organizational context. Galera-Zarco and Moretti (2025) show that the transformation of digital twin capabilities into organizational and innovation-related outcomes depends on the organizational context. Accordingly, value creation in the proposed model is conceptualized as a gradual transformation mechanism: Digital Twin Capabilities → Decision Support Capability → Decision Quality → Organizational Agility. Organizational performance is considered the subsequent and indirect outcome of this transformation chain.

3.5. Organizational Performance

At the final stage of the conceptual model, organizational performance represents the ultimate organizational outcome of the proposed value-creation process. Technological capabilities first need to become usable within decision-making processes and contribute to the organization's capacity to respond to changing conditions. Organizational performance is therefore positioned as a higher-level outcome that may emerge from the decision-related and organizational mechanisms developed in the preceding stages.

The proposed conceptual model suggests that the potential contribution of digital twin capabilities to organizational outcomes depends on how these capabilities are used within organizational processes. Galera Zarco and Moretti (2025) examine the role of digital twin capabilities in the implementation of digital service innovation, addressing the transformation of technological capabilities into organizational outcomes within an organizational context. The capacity of DT to provide data, visibility, analysis, or prediction does not itself constitute organizational performance; value depends on how these capabilities are utilized within organizational activities.

In the model, the link between organizational agility and organizational performance constitutes the final stage of this indirect value creation logic. Lu and Ramamurthy (2011), by examining the relationships between information technology capabilities, organizational agility, and firm performance within the same theoretical framework, demonstrate that agility is an important structure in understanding the transformation of information technologies into organizational outcomes. For the present model, this finding provides theoretical support for an indirect relationship in which enhanced responsiveness arising from decision support and decision quality may contribute to organizational performance. This relationship is also supported by the meta-analysis of Werder and Richter (2022), which provides an integrative assessment of the relationships between IT capability, organizational agility, and

performance and highlights the importance of agility in translating technological capabilities into organizational outcomes.

At this point, the business case for digital twin applications discussed by Bean et al. (2026) provides a complementary perspective. Particularly when digital twin technology is introduced into existing systems, the need to justify the investment in terms of value and resource requirements challenges the assumption that every DT implementation will automatically create organizational value. Thus, between technology implementation and performance outcomes lie factors such as the intended use, organizational requirements, and expected value. Digital twin investment therefore represents an organizational value-creation issue alongside its technical implementation requirements.

In this study, organizational performance is expanded to encompass multiple dimensions beyond a single operational indicator. The concept is used as a high-level structure encompassing outcomes such as improved operational activities, more efficient use of resources, more effective execution of processes, and the creation of broader organizational value. Because these dimensions are not empirically measured in the present study, they are treated as potential organizational outcomes of the proposed value-creation mechanism.

These outcomes remain proposed rather than empirically established; the model is intended to guide subsequent examination of the organizational conditions under which they may arise.

3.6. Integration of the Conceptual Model

The conceptual model developed in this study traces the organizational value of digital twin technology through the transformation of technological capabilities into organizational outcomes via decision-making processes. Digital Twin Capabilities form the starting point, while Organizational Performance represents the final outcome. Decision Support Capability, Decision Quality, and Organizational Agility connect these levels through the gradual value-creation mechanism presented in Figure 1.

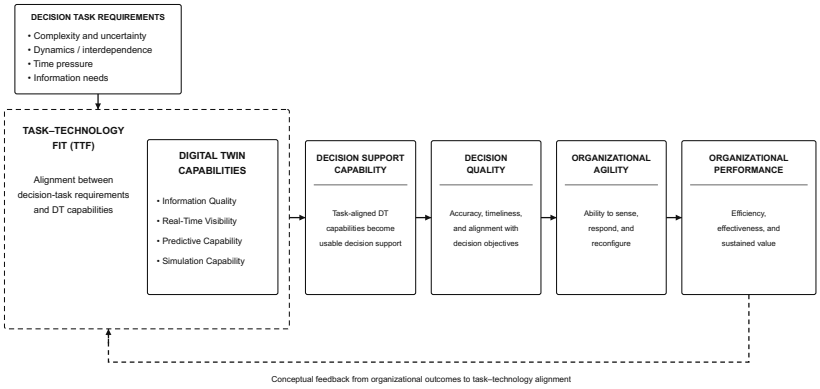


Figure 1. Conceptual Model
Source: Developed by the author based on the literature synthesis

In the first stage of the model, Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability represent the information and analytical resources that a digital twin can provide for decision support. However, as explained in Section 3.1 from a TTF perspective, the presence of these capabilities alone does not constitute decision support. A technological capability must fit the information and analytical requirements of the decision task. Decision Support Capability is conceptually distinct from TTF fit and functions in the model as the integrative mechanism through which task-aligned technological capabilities become usable in decision-making.

In the second stage, decision quality represents a potential decision-related outcome of decision support capability. The availability of information, predictions, or simulation outputs provided by DT does not automatically lead to higher-quality decisions. These outputs need to be related to the decision problem and used in evaluating alternatives. Decision quality subsequently captures how this support is reflected in the evaluation of information and alternatives within the decision process.

In the third stage, organizational agility represents a potential organizational-level outcome of this improvement in decision-making processes. The IS literature has established a relationship between IT capability and organizational agility (Lu & Ramamurthy, 2011), while more recent research has examined the relationship of digitalization and digital

capabilities with agility (Ciampi et al., 2022). However, the Decision Quality → Organizational Agility link proposed in this study is not presented as a direct empirical finding of these studies but as a conceptual relationship derived from the literature synthesis. Specifically, the model proposes that decisions based on more timely and relevant information and a more comprehensive consideration of alternatives may support an organization's capacity to respond appropriately and promptly to changing conditions.

In the final stage of the model, organizational performance represents the organizational value resulting from this transformation. Evidence that the translation of digital twin capabilities into organizational outcomes depends on context and on how these capabilities are used in organizational activities (Galera Zarco & Moretti, 2025) supports the argument that performance should not be treated as a direct consequence of technology. Similarly, the joint consideration of technological capabilities, organizational agility, and performance in the information systems literature highlights the importance of agility in the organizational value-creation process (Lu & Ramamurthy, 2011). Organizational performance represents the ultimate value outcome that may emerge through these decision-related and organizational mechanisms.

As illustrated in Figure 1, the model proposes a gradual value-creation mechanism that begins with digital twin capabilities and extends through decision support capabilities and decision quality to organizational agility and performance. This chain is not presented as a single causal model that has already been fully tested in the literature. The model is derived from the conceptual design logic of DSR and the task-technology fit perspective of TTF, integrating relationships addressed at different levels in the digital twin, decision support, and information systems literature. The conceptual contribution lies in integrating existing constructs into a framework that explains how DT capabilities can become decision-support capacity in appropriate tasks and how this transformation may extend to decision quality, organizational agility, and performance.

4. Research Agenda

The conceptual model developed in this study raises several questions for future research on digital twin-based decision support. The first research area concerns the conceptual and empirical validation of the Digital Twin Capabilities construct. The four dimensions are analytical constructs derived from the integration of functions identified across DT studies and have yet to be established as a standardized classification. Future research could examine whether these dimensions remain distinct across different sectors and decision contexts, how they interact with one another, and whether additional DT capabilities should be incorporated into the model. In particular, issues related to DT model validation, data reliability, and data management should be investigated as important conditions affecting the usability of these capabilities in decision-making processes (Bitencourt et al., 2025; Jeremiah et al., 2024).

The second research area concerns the empirical examination of the task–technology fit mechanism in DT-based decision support. The proposed model rejects the assumption that all DT capabilities create equal value across all decision tasks. Instead, it suggests that the fit between particular technological capabilities and the information and analytical requirements of a decision task is critical. Inyang and Taghikhah (2025), in their systematic review of digital twin-based decision support systems, show that DTs are used across different decision-making tasks and identify several research gaps in this area. For example, real-time visibility may be particularly important for time-sensitive operational tasks, whereas predictive capability may be more relevant when future conditions need to be assessed, and simulation capability may become more important when alternative interventions need to be compared. Future studies could compare different task types to test which DT capabilities provide a higher degree of fit under different decision conditions.

The third research area involves further developing the conceptual boundaries and measurement of decision support capability. Decision Support Capability is introduced in this study as an integrative mechanism

linking task–technology fit to the use of DT capabilities within decision processes; it is not an established component of TTF. Future studies could empirically examine functions associated with this capability, such as situation assessment, interpretation of analytical outputs, and comparison of alternatives. Moreover, the development of AI-enabled and increasingly cognitive DT structures raises an important research question concerning how the boundary between decision support and autonomous decision-making should be defined.

Finally, because the proposed Decision Support Capability → Decision Quality → Organizational Agility → Organizational Performance chain represents a set of conceptual propositions synthesized from different research streams, its causal structure requires empirical examination. Future studies could employ case studies, longitudinal research designs, and quantitative model testing to examine the organizational and environmental conditions under which these relationships emerge. In this way, digital twin research can move beyond describing what the technology is capable of doing toward explaining in which decision tasks, through which mechanisms, and under what conditions digital twins create organizational value.

5. Conclusion

The development of digital twin technology is moving beyond the digital representation of physical systems toward structures that integrate functions such as data integration, real-time monitoring, analytical assessment, prediction, and simulation within a common information environment. These technological advances alone, however, cannot account for the value of digital twins in organizational decision-making. Their contribution to decision support depends on how their capabilities are mobilized within the decision process.

Accordingly, based on the literature synthesis, this study proposes a gradual value-creation mechanism: Digital Twin Capabilities → Decision Support Capability → Decision Quality → Organizational Agility → Organizational Performance. Within this model, Information Quality,

Real-Time Visibility, Predictive Capability, and Simulation Capability are not treated as standardized DT dimensions but as an analytical synthesis of technological capabilities relevant to decision support. The TTF perspective explains why the value of these capabilities depends on their fit with the requirements of decision tasks, while decision support capability represents the conceptual mechanism developed in this study to explain how appropriate DT capabilities become functional in the decision-making process.

The relationships proposed in the model are not empirically validated causal relationships, but conceptual propositions derived from the integration of the existing literature. The main contribution of the study is therefore an MIS-based framework that traces the transformation of task-aligned technological capabilities into usable decision support and, through subsequent decision-related and organizational mechanisms, into organizational value.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

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Third-Party Materials and Permissions: Figure 1 was developed specifically for this chapter based on the literature synthesis and does not reproduce or adapt any third-party figure. The author confirms that no other third-party materials requiring permission have been used in the chapter.

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Chapter 3:

From Human–Computer Interaction to Human–AI Collaboration: A New Paradigm for Intelligent Management Information Systems

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Abstract

The rapid advancement of artificial intelligence (AI) is transforming the way individuals interact with digital technologies and Information Systems (IS), requiring a rethinking of some traditional assumptions underlying Human–Computer Interaction (HCI). In Management Information Systems (MIS), this transformation extends beyond the design of usable interfaces toward the development of intelligent systems that can actively support, augment, and collaborate with human users. This chapter examines the evolution from HCI to Human–AI Collaboration (HAC) and discusses its implications for the development of intelligent MIS. It first establishes the conceptual foundations of HCI, including human factors, user-centered design, usability, accessibility, and user experience (UX). It then examines the emergence of Human–AI Interaction (HAI) and the transition from computers as passive tools toward intelligent interaction partners. Building on this foundation, the chapter conceptualizes HAC through complementary human and AI capabilities, human oversight, AI-augmented decision-making, and increasingly autonomous AI systems. Particular attention is given to human-centered design, Generative AI, conversational and multimodal interfaces, intelligent UX, and the different roles humans may assume in AI-enabled environments, including interaction, evaluation, supervision, and, under appropriate conditions, collaboration with AI systems. The chapter further discusses ethical and organizational challenges, including algorithmic bias, privacy, transparency, accountability, automation bias, and human agency. It argues that the future of MIS will increasingly depend not only on technological intelligence but also on how effectively HAC is designed, governed, and integrated into organizational work.

Keywords: human–computer interaction, human–AI collaboration, management information systems, human-centered AI, generative AI

1. Introduction

The rapid development of digital technologies has fundamentally transformed the role of Information Systems (IS) within contemporary organizations. Management Information Systems (MIS) have traditionally been conceptualized as systems that collect, process, store, and deliver information to support managerial activities and organizational decision-making. However, the increasing integration of artificial intelligence (AI), machine learning, natural language processing (NLP), and other intelligent technologies is changing the nature of these systems. MIS are increasingly capable not only of providing information but also of interpreting data, generating insights, anticipating outcomes, supporting decisions, and interacting with users in increasingly adaptive ways. Consequently, the transformation of MIS is not merely a technological development; it also involves a transformation in how humans interact with, understand, control, and work alongside IS.

Human–Computer Interaction (HCI) provides an important theoretical and practical foundation for understanding this transformation. As an interdisciplinary field, HCI focuses on the design and evaluation of interactive technologies and on understanding how people use and experience such technologies (SIGCHI, n.d.). The evolution of HCI has historically followed changes in computing paradigms, from command-line interfaces and graphical user interfaces (GUI) to touch-based, mobile, ubiquitous, and multimodal interaction. The increasing intelligence of contemporary systems, however, introduces a qualitatively different interaction context. Rather than interacting solely with deterministic software through predefined interfaces, users increasingly interact with systems capable of inference, adaptation, recommendation, content generation, and autonomous action.

The emergence of Human–AI Interaction (HAI) illustrates this shift. AI-enabled systems introduce uncertainty, probabilistic outputs, changing system capabilities, and new forms of interaction that require users to understand not only what a system does but also when, why, and with what degree of confidence it should be relied upon. Amershi et al.

(2019) demonstrated the importance of explicitly considering these characteristics in the design of AI-infused interactive systems by proposing a set of general guidelines for HAI. Their work reflects an important transition within HCI: interaction design must increasingly account for systems that can make predictions, adapt their behavior, and produce outputs that may not always be deterministic or correct.

At the same time, the emergence of Human-Centered AI (HCAI) emphasizes that increasing system intelligence should not imply decreasing human control. Shneiderman (2020) argues for an approach in which high levels of automation can coexist with high levels of human control, while emphasizing human self-efficacy, responsibility, reliability, and trustworthy system design. This perspective is particularly relevant to MIS because organizational IS operate within decision-making structures in which accountability, human judgment, and organizational objectives remain important even when AI capabilities become increasingly sophisticated.

Recent research further indicates that HAI is developing into a broader research domain encompassing collaboration, competition, conflict, and symbiosis between humans and AI systems (Jiang et al., 2024). This development suggests that the relationship between humans and intelligent systems cannot be adequately understood solely through the traditional concept of interface interaction. The central question increasingly concerns how humans and AI can contribute complementary capabilities to shared tasks and decisions.

This transformation has direct implications for organizations and MIS. The implementation of AI in organizations involves organizational, technological, information-systems, and people-related dimensions, demonstrating that AI adoption cannot be understood exclusively as a technical implementation problem (Lee et al., 2023). Similarly, a systematic review of AI applications in MIS identifies intelligent process automation, predictive analytics, and NLP among the major areas of research, illustrating the expanding role of AI within management information environments (Stoykova & Shakev, 2023). These developments indicate

that intelligent MIS are increasingly becoming environments in which humans and AI jointly participate in information processing and organizational work.

This evolution raises a fundamental conceptual question: If IS are increasingly intelligent, adaptive, and capable of participating in decision-making, should humans still be conceptualized merely as users of IS? Recent IS research on Human–AI Collaboration (HAC) suggests that the answer requires a broader conceptualization of the relationship between humans and intelligent technologies. Seini et al. (2026), based on a systematic review of 137 IS studies, identify redefined human–machine relationships, effective interaction design, and organizational and societal implications as central themes in the emerging HAC literature.

Against this background, this chapter examines the transition from HCI to HAC and considers its implications for intelligent MIS. It argues that the evolution of MIS requires a broader understanding of the human role in intelligent information environments, where humans may interact with, evaluate, supervise, and, under appropriate conditions, collaborate with AI systems. The chapter therefore connects the theoretical foundations of HCI with HAI, HCAI, Generative AI, intelligent user experiences (UX), and organizational decision-making, while distinguishing HAC from other forms of HAI. It further examines the design, governance, and organizational implications of HAC and argues that the future of MIS will depend not only on technological intelligence but also on how effectively human–AI collaboration is designed, governed, and integrated into organizational work.

2. Foundations of Human–Computer Interaction

2.1. Concept and Scope of Human–Computer Interaction

HCI examines how people interact with computational systems and how these systems can be designed to support human goals, capabilities, and activities. Its development has drawn on computer science,

psychology, cognitive science, design, and ergonomics. The field therefore extends beyond interface appearance to consider how system characteristics influence human performance, understanding, behavior, and experience (Carroll, 2014).

Early HCI research focused on the relationship between human capabilities and system operation. Card et al. (1983) examined interaction through models of human information processing and task performance, while Norman and Draper (1986) emphasized user-centered approaches to system design. These foundations established a principle that remains relevant to intelligent IS: system design should account for the characteristics of the people who use it rather than treating interaction as a purely technical problem.

The scope of HCI subsequently expanded toward usability, UX, accessibility, context, and human-centered design. Interaction became understood as part of a broader relationship between people, technology, tasks, and environments. This perspective is particularly relevant to MIS because IS operate within organizational settings rather than as isolated technological artifacts.

2.2. Evolution of Human–Computer Interaction

The evolution of HCI reflects successive changes in how people communicate with computational systems. Early computing environments required users to formulate commands according to relatively rigid syntactic rules. GUIs introduced visual representations, menus, windows, icons, and pointing devices, shifting interaction from command recall toward recognition and direct manipulation. As the Web, mobile computing, touch interfaces, ubiquitous computing, and multimodal technologies developed, interaction moved beyond the conventional desktop and became increasingly embedded in everyday activities and organizational processes.

This evolution also changed the criteria for successful interaction. Functional correctness alone was no longer sufficient. Users expected systems to be understandable, efficient, consistent, responsive, and

supportive of their goals. Usability engineering emerged in response to these expectations, providing systematic approaches to usability evaluation and design (Nielsen, 1994). Bevan (2001) similarly showed how HCI and usability standards expanded beyond interface characteristics to include context of use, development processes, and organizational capabilities.

For MIS, this evolution is significant because IS are embedded in work practices, decision processes, communication structures, and organizational routines. Interaction quality can therefore affect not only individual task performance but also how effectively an IS supports organizational objectives.

2.3. Human Factors, Cognition, and Interaction

Human factors provide an important foundation for understanding why some interactions are easier, safer, or more effective than others. Users have limited attention, working memory, and information-processing capacity, and these constraints influence how information should be presented and how tasks should be structured. HCI consequently considers perception, attention, memory, learning, problem solving, and decision-making.

Mental models are particularly important because users form expectations about how systems work. When system behavior corresponds with these expectations, interaction becomes easier to understand and predict. Poorly designed systems can create mismatches between expectations and actual behavior, increasing errors and cognitive effort. Feedback, consistency, visibility, and clear system status help users understand what has occurred and what actions remain possible.

These principles remain relevant as systems become more intelligent. AI introduces additional cognitive demands because users may need to interpret outputs whose behavior is less predictable than that of conventional software. Understanding human cognition therefore remains important for designing interactions that allow users to interpret, question, and appropriately respond to system behavior.

2.4. User-Centered Design and User Experience

User-centered design shifted system development from designing technology first and expecting users to adapt toward involving users and their needs throughout the design process. Norman and Draper (1986) emphasized designing around users and their activities, while later approaches placed greater emphasis on iterative evaluation and context of use.

UX extends the discussion beyond whether a system can be used successfully. Hassenzahl and Tractinsky (2006) describe UX as encompassing users' perceptions and responses arising from interaction with a system, including pragmatic and experiential qualities. An MIS may therefore be technically functional and usable while still producing a poor experience if it creates unnecessary effort, uncertainty, frustration, or a lack of confidence.

This distinction becomes increasingly important as IS take on more active roles. When systems provide recommendations, generate content, or adapt to users, the experience depends not only on interface characteristics but also on how system behavior is perceived and interpreted.

2.5. Usability, Accessibility, and Inclusive Design

Usability remains a fundamental HCI concept. Nielsen (1994) associates usability with characteristics such as learnability, efficiency, memorability, error management, and satisfaction. ISO 9241-11 (International Organization for Standardization [ISO], 2018) similarly defines usability in relation to the extent to which specified users can achieve specified goals with effectiveness, efficiency, and satisfaction within a specified context of use.

Accessibility extends these concerns to people with different abilities, technologies, and interaction requirements. Inclusive design recognizes that users differ in physical, sensory, cognitive, cultural, and

contextual characteristics. Designing for accessibility therefore contributes to the broader goal of making systems usable across diverse conditions.

For intelligent MIS, these principles provide an important foundation but do not fully resolve the emerging interaction problem. Traditional HCI has primarily focused on designing and evaluating interactions between people and computer systems, with particular attention to usability, user needs, interaction design, and effective system use. AI-enabled systems can interpret intentions, generate content, provide recommendations, adapt to interaction histories, and increasingly perform actions. Interaction consequently becomes more adaptive, dynamic, and reciprocal.

The central question therefore shifts from how interfaces should respond to human commands toward how interaction should be designed when the computational system can interpret, generate, recommend, and increasingly act. This transition provides the conceptual basis for HAI, while also creating a further question: when does interaction with an AI system become HAC within organizational work?

3. From Human–Computer Interaction to Human–AI Interaction

3.1. From Predictable Interfaces to Intelligent Interaction

The transition from HCI to HAI is not simply a change in interface technology. It reflects a change in the system with which people interact. Traditional HCI has primarily focused on the design and evaluation of interactions between people and computer systems, including the relationship between user actions, system processes, and outputs. AI-enabled systems introduce a different interaction context because they can interpret intent, infer patterns, generate content, adapt their behavior, and produce outputs whose exact form may not always be anticipated in advance.

This distinction is particularly important when AI is embedded in MIS. A conventional IS may present a predefined report or execute a query according to established rules. An AI-enabled system may instead summarize information, identify relevant patterns, formulate recommendations, or generate a response to a natural-language request. The user is consequently no longer interacting only with a predefined set of functions. The user is interacting with a system that interprets the request and determines how to respond within the boundaries of its model, available information, and operational context.

Amershi et al. (2019) identify these characteristics as central challenges for HAI design. Their guidelines emphasize that AI systems introduce issues related to imperfect performance, uncertainty, system behavior over time, and the need for users to understand and control AI-supported functionality. Interaction design therefore needs to accommodate not only successful system behavior but also uncertainty, failure, correction, and changes in system performance.

3.2. From System Response to Adaptive Interaction

The shift toward intelligent interaction also changes the role of feedback. In conventional interfaces, feedback primarily communicates the result of an action. With AI-enabled systems, feedback can become part of an ongoing interpretive process. Users may need to understand why a recommendation was produced, whether an output is reliable, how an error occurred, and what can be done to correct or refine the result.

Interaction can consequently become iterative and adaptive. A user may provide an initial instruction, inspect the AI-generated response, revise the instruction, add contextual information, reject part of the output, and continue the exchange until the result becomes useful. Rather than following a simple input–processing–output sequence, the interaction develops through repeated cycles of interpretation, evaluation, correction, and adaptation.

Raees et al. (2024) argue that HAI research needs to move beyond approaches focused primarily on explaining AI decisions or allowing users to contest them. Their analysis points toward more interactive forms of AI in which users have greater agency and can influence how systems behave. This is particularly relevant to MIS because organizational users often possess contextual knowledge that may not be available to the system. Effective HAI therefore requires mechanisms through which users can provide context, correct assumptions, and shape subsequent system responses.

3.3. The Changing Role of the User

As AI becomes more capable of interpreting and generating information, the conventional concept of the user becomes increasingly limited. In traditional HCI, the user is generally understood as the person who operates a technological system to accomplish a task. In HAI, the user may also evaluate AI outputs, provide feedback, correct errors, formulate instructions, supervise system behavior, and decide whether an AI recommendation should be accepted or rejected.

This does not make the human passive. In many situations, greater system intelligence increases the importance of human judgment. Users need to understand the capabilities and limitations of the system and retain meaningful control over how its outputs are used. Human agency therefore becomes a central design concern. A system that performs more functions but leaves users unable to understand, challenge, or redirect its behavior may increase automation without necessarily improving the quality of interaction.

Jiang et al. (2024) show that contemporary HAI research encompasses several forms of human–AI relationships, including collaboration, competition, conflict, and symbiosis. HAI therefore does not imply collaboration by definition. The nature of the relationship depends on the task, the distribution of capabilities, the degree of system autonomy, and the consequences of errors. This distinction becomes particularly important in MIS, where the objective is often not simply to

automate an activity but to improve how information, judgment, and technological capabilities are combined in organizational work.

3.4. Toward Human–AI Interaction in MIS

The significance of the transition from HCI to HAI for MIS lies in the changing role of the IS itself. When systems can interpret requests, generate analyses, recommend actions, and adapt to interaction, the interface becomes more than a mechanism for accessing information. It becomes a setting in which information is interpreted, evaluated, negotiated, and potentially transformed into organizational action.

This development creates a conceptual bridge between interaction and collaboration. HAI concerns how humans and intelligent systems interact and influence one another, whereas collaboration concerns the coordination of their contributions within a shared organizational task or decision. This distinction provides the conceptual foundation for examining the conditions under which HAI develops into HAC in MIS.

4. From Human–AI Interaction to Human–AI Collaboration

4.1. From Interaction to Collaboration

HAI does not necessarily imply HAC. An AI system may respond to requests, generate information, or provide recommendations without becoming a collaborator in a meaningful organizational sense. Collaboration involves coordinating human and AI capabilities around an organizational task or decision (Wang et al., 2026).

The distinction is better understood through the nature of the work than through the sophistication of the technology. When an employee asks an AI system to summarize a document and uses the result without further interaction, the relationship remains largely tool-oriented. A different relationship emerges when the employee evaluates the summary, provides organizational context, questions an interpretation, requests revisions, and combines the result with professional judgment. The AI contribution is

then integrated into a broader task rather than simply consumed as an output.

For MIS, this distinction matters because adding an AI capability to an existing IS does not by itself create collaboration. The distribution of responsibilities, coordination of contributions, and decision authority determine whether an AI-supported activity constitutes collaboration.

4.2. Complementary Capabilities and Task Allocation

The rationale for HAC lies in combining capabilities that are difficult to reproduce within a single actor. AI systems can process large volumes of information rapidly, identify patterns, generate alternatives, and perform repetitive analytical activities. Humans contribute contextual knowledge, professional experience, social understanding, ethical reasoning, and organizational judgment.

The value of this combination depends on the task. A manager may understand institutional constraints while an AI system can compare historical cases, identify patterns, and generate alternative scenarios. Collaboration becomes valuable when these contributions are coordinated rather than when one simply replaces the other.

Hao et al. (2024) found that Generative AI can reduce cognitive burden and support decision-making in situations involving information overload, while also identifying risks associated with over-reliance. Effective collaboration therefore does not require maximizing AI involvement. Responsibility should be distributed according to task characteristics and the relative strengths and limitations of human and AI contributions.

Shneiderman (2020) similarly emphasizes combining automation with meaningful human control. Automation transfers execution to a system; augmentation extends human capabilities; collaboration coordinates human and AI contributions around a task. These arrangements may coexist within the same MIS workflow. A system may

automate data preparation, augment managerial analysis, and require human judgment at the decision stage.

Task allocation is consequently a central design issue. Activities should not be assigned to AI simply because the technology can perform them, and human involvement should be determined not only by the value it adds but also by task complexity, ambiguity, contextual requirements, consequences of error, AI reliability, accountability, and the need for appropriate human oversight. Decision authority should be aligned with these factors and with the potential consequences of the action.

4.3. Human Agency, Control, and Calibrated Reliance

Task allocation also determines how much control humans retain over AI-supported processes. In a human-in-the-loop arrangement, human judgment is incorporated directly into the process, such as when an AI recommendation requires approval. In a human-on-the-loop arrangement, the system operates with greater autonomy while humans monitor its behavior and intervene when necessary.

Human agency cannot be reduced to the existence of an override function. A control mechanism has limited value if users cannot recognize when intervention is necessary, lack sufficient information to evaluate an output, or lack authority to change the resulting action. Meaningful control requires practical capacity to understand, evaluate, and influence AI-supported outcomes.

Effective collaboration also requires calibrated reliance. Users should rely on AI when its capabilities are appropriate and question its outputs when uncertainty, limitations, or contextual factors warrant caution. AI systems may produce fluent and persuasive outputs even when information is incomplete or incorrect. Excessive reliance can therefore shift practical decision authority toward the system without a formal transfer of responsibility.

The opposite problem can occur when users reject potentially useful AI recommendations because of previous failures or limited understanding of system capabilities. The objective is not to maximize trust but to establish an appropriate relationship between system capability, user expectations, and human judgment.

4.4. AI Agents, Autonomy, and Emerging Forms of Collaboration

AI agents introduce a further change because AI systems can increasingly carry out sequences of actions rather than responding only to individual requests. An agent may interpret a goal, determine intermediate steps, retrieve information, use available tools, and execute defined actions with limited human intervention.

Greater autonomy increases the importance of delegation, authorization, monitoring, escalation, and accountability. An organization may allow an agent to gather information and prepare a recommendation while requiring human authorization before a financial, personnel, or customer-facing action is executed.

Seini et al. (2026) identify AI copilots and agentic AI as developments reshaping HAC. Increasing autonomy should not, however, be equated with collaboration. An autonomous system can simply automate a process. Collaboration exists when AI activity is connected to human contribution within an organizational task and when decision authority remains appropriate to the consequences of the action.

For the purposes of this chapter, HAC in MIS is understood as a structured work arrangement in which human and AI capabilities are deliberately coordinated to accomplish an organizational task or decision, with responsibilities and decision authority distributed according to task characteristics, system capabilities, and organizational context.

This perspective changes the central question for MIS. Instead of asking only whether AI can perform a particular task, organizations need to determine how that task should be structured when both human and

AI capabilities are available. The resulting IS becomes an intelligent work environment in which computational capabilities, human expertise, organizational context, and decision authority are deliberately brought together.

5. Human-Centered Design of Intelligent MIS

5.1. From Human-Centered Design to Human-Centered AI

The transition from HCI to HAC changes what needs to be considered during system design. User-centered design emphasizes users, their goals, tasks, and contexts throughout development. Human-centered design extends this perspective by considering people, their broader contexts, and the effects of technology across its lifecycle. ISO 9241-210 (ISO, 2019) places human needs, contexts of use, iterative development, and human involvement at the center of interactive system design.

When AI becomes an active component of an IS, the design problem becomes less predictable. Outputs may vary across situations, contain uncertainty, and change according to data, model behavior, or interaction history. HCAI provides a perspective for addressing these conditions. Shneiderman (2020) emphasizes meaningful automation, human control, reliability, and accountability.

HCAI should not be treated as another term for HAC. HCAI concerns principles for designing AI systems around human needs and capabilities, whereas HAC concerns how human and AI capabilities are coordinated within a task. For intelligent MIS, the challenge is to translate human-centered principles into systems that remain useful and understandable while accommodating AI uncertainty.

5.2. Designing for Human Agency, Transparency, and Uncertainty

Human control becomes particularly important when AI systems influence decisions or perform actions. An intelligent MIS should allow users to understand relevant system behavior, intervene when necessary, and determine whether an AI recommendation or action should be accepted. Amershi et al. (2019) emphasize communicating AI capabilities and limitations, providing appropriate feedback, and supporting users in correcting or overriding system behavior.

Transparency is valuable insofar as it enables users to understand, evaluate, and appropriately influence AI-supported outcomes. Transparency concerns the visibility of relevant system behavior, whereas explainability concerns users' ability to understand why a particular output or recommendation was produced. A manager evaluating an AI recommendation may not need a technical description of the model architecture. More useful information may concern the factors influencing the recommendation, the evidence considered, and relevant limitations. Raees et al. (2024) similarly emphasize user agency in Interactive AI, extending the discussion beyond explanation toward the user's ability to influence and contest AI behavior.

Meaningful agency also depends on the character of AI outputs. Unlike many conventional IS functions, AI outputs are not fully predetermined. They may vary across inputs and contexts and can contain uncertainty even when presented confidently. Human-centered design should therefore communicate relevant uncertainty and provide opportunities to question, compare, or revise system outputs. An override mechanism is insufficient if users cannot recognize when intervention is necessary or lack the information and authority required for evaluation.

5.3. Adaptive Interfaces and Organizational Context

AI can transform interfaces from relatively fixed structures into adaptive environments. Intelligent MIS may adjust information presentation, recommend actions, anticipate information needs, and personalize interaction according to user behavior or organizational context. Such capabilities can reduce the effort required to locate and interpret information.

Adaptation nevertheless creates a tension between responsiveness and predictability. If system behavior changes substantially without an understandable reason, users may find it difficult to develop reliable expectations. Personalization can create similar problems when recommendations are based on assumptions that users cannot inspect or modify. Human-centered design should therefore make important forms of adaptation visible and adjustable.

Organizational context adds another layer. Decisions are rarely determined by structured data alone. Policies, informal knowledge, professional responsibilities, organizational culture, stakeholder relationships, and situational factors can influence interpretation. An AI system operating primarily on available data may therefore produce technically plausible outputs that remain incomplete from a managerial perspective. Technical intelligence does not by itself produce organizational intelligence.

Intelligent MIS should provide ways for users to contribute contextual information that is not captured directly in the underlying data. Editable assumptions, contextual inputs, scenario comparison, feedback, and correction mechanisms can connect computational analysis with organizational knowledge. The objective is not simply to make the AI model more capable, but to make its outputs interpretable within actual organizational circumstances.

5.4. Designing Collaborative Intelligent Management Information Systems

These considerations shift design from the interface alone toward the relationship between people, AI capabilities, and organizational processes. Designers need to consider how AI behavior is communicated, how users contribute context, how outputs can be evaluated and corrected, and how intelligent functions fit within existing workflows. The quality of an intelligent MIS therefore depends on more than model performance or interface usability.

Taken together, these principles suggest that intelligent MIS should align AI capabilities with task characteristics, provide sufficient visibility into system behavior, communicate relevant uncertainty, accommodate organizational context, and allow users to evaluate and influence important outputs. Adaptation should remain understandable and adjustable rather than becoming an opaque feature of the system.

The broader task is to create an intelligent work environment in which computational capabilities, human expertise, organizational knowledge, and system behavior function together without making the human role merely symbolic. Intelligent MIS should support efficient interaction as well as informed evaluation, contextual interpretation, and responsible use of AI.

This design perspective provides a foundation for understanding Generative AI. As AI systems become capable of producing text, analyses, and other forms of content in response to natural-language instructions, the design challenge extends toward new forms of interaction and experience.

6. Generative AI and the Transformation of User Experience

6.1. From Information Retrieval to Generative Interaction

Generative AI changes interaction with IS by allowing users to request, transform, and produce information without relying entirely on predefined system functions. Conventional MIS interfaces organize access through menus, forms, queries, dashboards, and reports. Generative AI allows users to describe an information need in natural language and ask the system to interpret that need and produce a response.

The difference is more fundamental than replacing menus with conversational interfaces. In a conventional system, the path from request to result is largely determined by the interface and application logic. With Generative AI, users can describe an objective without necessarily knowing which technical function should accomplish it. The system interprets the request and determines an appropriate response. A manager might ask for changes in quarterly sales, request an explanation of significant deviations, and then ask for the findings to be prepared for a management meeting.

The key change is therefore not merely how users access system functions, but how users express goals when the system can interpret and operationalize those goals. Interaction becomes more open-ended. Summarization, comparison, classification, explanation, drafting, and synthesis can occur within the same exchange. Luera et al. (2024) identify conversational and iterative interaction as important characteristics of emerging Generative AI interfaces.

Greater flexibility also creates a problem of interpretation. A natural-language request can be incomplete or ambiguous, while a generated response may appear convincing even when the system has misunderstood the user's intention. Interfaces therefore need to support

clarification and correction. Amershi et al. (2019) emphasize helping users understand system capabilities, recover from errors, and appropriately guide AI behavior.

6.2. Prompting, Co-Creation, and the Changing Nature of User Experience

Generative AI changes what users do during an interaction. Instead of simply selecting functions, users formulate instructions, provide context, examine generated material, identify problems, and decide how the interaction should continue. Prompting therefore becomes part of the work involved in expressing and refining an information need.

A typical interaction may develop through several rounds. A user begins with a broad request, receives an output, recognizes that an organizational constraint is missing, provides additional context, and evaluates a revised result. Generative AI may reduce operational effort while creating new forms of interpretive and evaluative work.

This change is particularly visible in managerial and knowledge-intensive activities. A manager preparing an analysis of customer complaints might ask the system to identify recurring issues, specify a customer segment, distinguish operational problems from product-related complaints, and request implications for the following quarter. The usefulness of the interaction develops through the user's ability to recognize what is missing and direct the system toward a more relevant result.

Generative AI also allows users to participate directly in producing organizational artifacts. Reports, presentations, summaries, and scenarios can be developed through iterative exchanges. Research on Generative AI in UX and design has identified applications in ideation, prototyping, and evaluation while emphasizing human assessment and refinement (Luo, 2025; Muehlhaus & Steimle, 2024).

This creates a more complicated understanding of UX. A successful experience cannot be assessed only by how quickly a system produces an

output. Human decision makers need to determine whether that output is accurate, relevant, sufficiently complete, and appropriate for its intended use. A report generated within minutes may save production time while requiring substantial verification. Generative AI can therefore redistribute effort rather than simply eliminate it.

Co-creation emerges from this redistribution. Humans contribute objectives, contextual knowledge, preferences, evaluation, and judgment, while AI contributes generation, synthesis, variation, and rapid transformation of information. Co-creation should not automatically be equated with HAC. Collaboration requires coordinated contributions, an organizational task or objective, and an appropriate distribution of responsibilities.

6.3. From Frictionless User Experience to Collaborative Experience

Generative AI also challenges the assumption that reducing interaction friction is always desirable. Fewer steps and faster responses can improve an experience, but eliminating every interruption may also remove opportunities to inspect, question, or reconsider an AI-generated result.

This distinction is particularly important in intelligent MIS. An AI system may generate a financial analysis and incorporate it into a managerial report with almost no additional interaction. The process appears efficient, but the user may have little opportunity to examine assumptions, data limitations, or unusual findings. A review step can introduce additional interaction while improving decision quality. Malaguti et al. (2025) therefore argue for a more nuanced understanding of interaction friction in Generative AI environments.

Interaction friction should consequently be evaluated according to its function rather than minimized by default. Friction that supports verification, reflection, or accountability may contribute to better organizational outcomes. Generated content can be fluent and persuasive even when information is incomplete or incorrect. UX in Generative AI

environments must therefore support verification, correction, and calibrated reliance.

The same principle applies to co-creation. An AI system can generate alternatives, revise a document, or propose interpretations, but human decision makers retain responsibility for evaluating which contributions are appropriate within their role and decision context. The relationship becomes more clearly collaborative when AI contributions and human judgment are connected within an organizational task and the responsibilities of each participant are understood.

This transformation represents a movement from navigation-centered UX toward interaction-centered and increasingly collaboration-oriented UX. Conventional MIS interfaces emphasize navigation and retrieval, whereas Generative AI introduces instruction, generation, evaluation, and refinement as central components of the experience. When these activities become embedded in organizational tasks, UX becomes part of a broader Human–AI collaborative experience.

Generative AI therefore represents more than a change from graphical interfaces to conversational ones. Users are no longer only navigating information structures; they are interacting with systems that can interpret requests and produce new content. For MIS, the central UX question becomes how effectively an intelligent system supports the movement between human intention, AI generation, critical evaluation, and organizational action.

7. Human–AI Collaboration in Management Information Systems

7.1. Human–AI Collaboration in Managerial Decision-Making

MIS have traditionally supported managerial decision-making by collecting, processing, organizing, and presenting information. AI extends this role by contributing directly to analysis, prediction, recommendation,

and scenario generation. An AI-enabled MIS can identify patterns, compare alternatives, summarize large information sets, and formulate possible courses of action. The manager is consequently no longer limited to selecting information from predefined reports; decision-making can involve an exchange between managerial judgment and computational analysis.

The value of this arrangement as HAC depends on whether human and AI contributions are coordinated within a shared organizational decision process, with responsibilities and decision authority appropriately distributed. Hao et al. (2024) show that Generative AI can reduce cognitive burden and support decision-making in situations involving information overload, while also identifying risks associated with excessive reliance on AI-generated outputs. The relevant question is therefore not whether AI should make decisions instead of managers, but under what conditions its analytical capabilities can be coordinated with managerial judgment within a shared decision process.

Decision authority remains important. AI may analyze data, estimate outcomes, simulate alternatives, or generate recommendations without having authority over the final decision. Human decision makers can introduce contextual knowledge, question assumptions, reject recommendations, and authorize consequential actions. The appropriate balance depends on the task, system reliability, uncertainty, and consequences of error.

7.2. Human–AI Collaboration in Knowledge Work and Organizational Processes

HAC can also emerge in knowledge-intensive activities such as reporting, document analysis, forecasting, information synthesis, communication, and organizational analytics when human and AI contributions are coordinated within a shared organizational task. The important change is not simply that individual tasks become faster. The sequence and distribution of work can change when AI performs selected activities within a larger organizational process.

A knowledge worker may define a problem, use AI to identify relevant information, examine alternative interpretations, provide organizational context, and integrate validated results into a final report. Such a process constitutes HAC when these contributions are deliberately coordinated around a shared organizational objective and responsibilities and decision authority are appropriately distributed. Different stages of the same process can therefore involve different levels of human and AI participation. Seini et al. (2026) identify AI copilots and increasingly agentic systems as developments reshaping the relationship between AI and organizational work.

An AI capability that performs well in isolation may have limited value if it does not fit the activities surrounding it. Information dependencies, approval requirements, escalation procedures, monitoring, and responsibility for reviewing outputs all influence how AI should be incorporated. The integration of AI should therefore be evaluated at the workflow level, since the organizational effects of an AI capability depend on how its outputs enter subsequent human and system activities.

Not every form of AI-supported work constitutes HAC. Collaboration emerges when these contributions are coordinated within a shared organizational task and responsibilities are appropriately distributed. Employees may supervise outputs, provide contextual information, correct system assumptions, determine when further analysis is needed, and integrate AI-generated material with organizational knowledge. AI may perform information-intensive activities, generate alternatives, monitor patterns, or initiate defined process steps. The distribution can vary across different stages of the same workflow.

This development broadens the role of MIS. Decision-support systems, business intelligence platforms, knowledge-management systems, enterprise workflows, and organizational analytics can increasingly become environments in which human and AI capabilities are coordinated. The relevant question is therefore not only how employees interact with an AI feature, but how AI participation changes the structure of organizational work.

7.3. Organizational Value, Performance, and the Limits of Collaboration

The organizational value of HAC should not be assessed solely through the amount of work performed by AI or the time saved through automation. AI capability does not automatically translate into organizational value. More meaningful measures include decision quality, knowledge quality, responsiveness, productivity, innovation, service quality, and the effective use of managerial expertise.

AI can redistribute work rather than simply eliminate it. A system may accelerate information processing while increasing the verification required from employees. A Generative AI system may produce a report within minutes while requiring substantial effort to check its assumptions, calculations, and contextual relevance. Productivity gains should therefore be evaluated across the complete human–AI workflow rather than at the level of an individual AI-assisted task.

The appropriate degree of AI participation also depends on task characteristics. Routine and information-intensive activities may benefit substantially from AI assistance, whereas tasks involving ambiguous objectives, sensitive relationships, ethical judgments, or significant consequences may require stronger human involvement. Task structure, uncertainty, contextual dependence, system reliability, and the consequences of error should influence decisions about delegation and oversight.

HAC in MIS should therefore be understood as an organizational design problem rather than an objective of maximizing AI adoption. The aim is to determine where AI capabilities can improve organizational work and where human expertise, judgment, and authority need to remain central. Intelligent MIS can create greater value when AI analysis and generation are connected to human context and evaluation, organizational workflows, and accountable decision-making.

Combining human and AI capabilities also creates new questions concerning accountability, oversight, fairness, and the governance of AI-

supported organizational action. These questions become increasingly important as AI systems move from analytical support toward more autonomous participation in organizational processes, providing the basis for the ethical and governance challenges examined in the following section.

8. Ethical Challenges and Future Directions of Human–AI Collaboration

8.1. Ethical Challenges of Human–AI Collaboration

The increasing integration of AI into organizational decision-making and work processes creates ethical challenges that cannot be addressed through technical performance alone. When AI systems influence recommendations, generate organizational knowledge, or perform actions, questions arise concerning fairness, privacy, transparency, accountability, and human control. These concerns become more significant as AI moves from providing information toward participating directly in decisions and organizational processes.

Algorithmic bias remains a central concern. AI systems can reproduce or amplify patterns contained in training data, organizational records, or existing decision processes. In MIS, this may affect recruitment, customer evaluation, resource allocation, risk assessment, or managerial recommendations. Human involvement does not automatically eliminate such problems. If users routinely accept AI recommendations without examining their assumptions, existing biases may become less visible while continuing to influence outcomes.

Privacy presents another challenge. Intelligent MIS can process large volumes of organizational and individual data, while Generative AI and agentic systems may require access to multiple information sources to perform increasingly complex tasks. Integrating information across systems can create substantial value, but it also increases the consequences

of inappropriate access, secondary use, or disclosure. HAC therefore requires clear boundaries concerning what information AI systems can access, how that information can be processed, and under what conditions outputs can be shared.

Accountability becomes particularly difficult when an organizational outcome results from a combination of AI recommendations, human judgment, organizational rules, and automated actions. HAC can consequently create forms of distributed responsibility in which no single technological or human action fully explains the final outcome. Responsibility must nevertheless remain connected to identifiable organizational roles, decision authority, and governance mechanisms. Transparency and explainability can support this process, but an explanation alone does not create accountability. A human may receive an explanation without having sufficient authority to reject an AI recommendation, or may formally retain responsibility without having enough information to evaluate the output.

Human agency is therefore a central ethical requirement. The important question is not whether a human remains somewhere in the process, but whether that person retains meaningful capacity to influence consequential outcomes. Automation bias and over-reliance can gradually shift practical decision authority toward AI even when formal responsibility remains with a human. Governance mechanisms such as approval requirements, access controls, monitoring, audit trails, escalation procedures, and clearly assigned responsibility are therefore necessary components of intelligent MIS.

8.2. Future Directions: Toward Governed Human–AI Systems

Future forms of HAC are likely to involve increasingly adaptive and autonomous systems, although greater autonomy should not be understood as inherently constituting a more advanced form of collaboration. AI agents may move beyond generating recommendations toward planning and executing sequences of actions across organizational

systems. Their operation can increasingly follow a cycle of planning, acting, observing results, and revising subsequent actions. Such capabilities could substantially expand the role of intelligent MIS, particularly in information-intensive and repetitive processes. Greater autonomy, however, also makes the boundaries of delegation, monitoring, escalation, and accountability more consequential.

The central issue is therefore not autonomous AI alone but governed autonomy. Future intelligent MIS will need to establish conditions under which autonomous action remains observable, controllable, and accountable. The appropriate degree of human oversight may vary according to task characteristics, system reliability, potential consequences, and organizational risk. A low-risk routine activity may permit extensive delegation, whereas a consequential managerial decision may require direct human involvement and explicit authorization.

AI literacy will also become an organizational capability. Effective collaboration requires more than knowing how to formulate prompts. Managers and employees need to understand AI capabilities and limitations, evaluate generated outputs, recognize uncertainty, identify inappropriate automation, and determine when human intervention is required. Organizational AI literacy should therefore encompass judgment and critical evaluation as well as operational skills.

8.3. From Human–Computer Interaction to Governed Human–AI Collaboration

The progression examined throughout this chapter represents more than a sequence of technological developments. HCI established the importance of designing systems around human capabilities, goals, usability, and experience. HAI extended this perspective to systems that can interpret, generate, adapt, and increasingly act. HAC goes a step further by asking how human and AI capabilities should be combined within shared tasks and organizational processes.

From this perspective, the future of MIS is not simply a matter of increasing system intelligence or autonomy. Intelligent systems need to be designed around human agency, organizational context, complementary capabilities, appropriate task allocation, and accountable governance. The central design question consequently shifts from what AI can do to what AI should do, when humans should intervene, and how responsibility should be maintained when both contribute to organizational decisions and actions.

The evolution from HCI to HAC therefore reflects a fundamental transformation in the relationship between humans, intelligent systems, and organizational work. The future of MIS will depend not simply on more intelligent automation, but on governed forms of HAC in which AI capabilities are combined with human judgment, organizational knowledge, meaningful human control, and accountable decision-making.

9. Conclusion

This chapter contributes to the understanding of intelligent Management MIS by distinguishing HCI, HAI (HAI), and HAC as related but distinct concepts. Its central argument is that the integration of AI into organizational systems does not automatically establish collaboration. Rather, HAC emerges when human and AI capabilities are deliberately coordinated within a shared organizational task or decision, with responsibilities and decision authority appropriately allocated. The central issue is therefore no longer limited to how people use IS, but also concerns how different forms of HAI can be structured and, where appropriate, developed into effective HAC within organizational tasks and decision processes.

For MIS, this distinction shifts attention from AI capability alone toward the design of human–AI relationships within organizational contexts. Effective systems must account for uncertainty, contextual knowledge, human judgment, and the capacity to evaluate and influence AI-supported outcomes. Human agency and meaningful control are therefore not separate design considerations but essential conditions for

ensuring that intelligent systems support rather than undermine organizational decision-making.

The chapter also highlights the implications of intelligent technologies for MIS design and UX. As AI systems generate content, provide recommendations, and adapt to user input, system quality depends not only on usability but also on the interpretability, reliability, and appropriate use of AI outputs. Designing effective intelligent MIS consequently requires attention to how users evaluate system responses, provide contextual information, and integrate AI-generated results into their work.

At the organizational level, HAC offers a framework for examining how human expertise and AI capabilities can be combined in managerial decision-making, knowledge work, and business processes. Its organizational value depends on the fit between task requirements and the capabilities of each contributor, as well as on workflow integration, system reliability, and the allocation of responsibilities. The relevant objective is not to maximize automation, but to organize human and AI contributions in ways that improve task performance while preserving appropriate decision authority.

These implications make governance integral to intelligent MIS. Organizations need arrangements that address bias, privacy, accountability, and oversight while ensuring that individuals responsible for consequential decisions have sufficient information and authority to evaluate AI-supported outcomes. As AI systems become more autonomous, governance must also clarify the boundaries of delegation, the conditions for human intervention, and the assignment of responsibility for resulting actions.

The chapter's central contribution is to position HAC not as an inevitable endpoint of technological development, but as an organizational arrangement that must be deliberately designed and governed. This perspective provides a basis for future MIS research examining how task characteristics, human expertise, system capabilities, and governance mechanisms shape the outcomes of AI-supported work. Ultimately, the

contribution of intelligent MIS will depend not simply on advances in AI, but on how effectively organizations align technological capabilities with human judgment, organizational objectives, and accountable decision-making.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

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Chapter 4:

Bibliometric Analysis of Cybersecurity Complexity in Cloud Computing

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Abstract

The growth and integration of cloud computing with other advanced technologies (such as Artificial Intelligence (AI) and other security technologies and architectures) have introduced different cybersecurity challenges and opportunities that require academic investigation. This research conducts a bibliometric analysis of 1,583 papers from Scopus database between 2010 to 2026 trying to address four main research aims: (1) publication growth and productivity, (2) active contributors in the field, (3) themes and evolution of cloud security, and (4) emerging and research directions. The findings reveal an exponential growth, with annual output rising from 3 papers in 2010 to 358 in 2025, highlighting an annual growth rate exceeding 30%. Keyword analysis also reveals technical security evolutions: from cloud architecture and basic security (2010–2015), through threat, privacy, risk and intelligent detection (2016–2020), to current state dominated AI-driven approaches and other cutting edge technologies such as blockchain, edge computing, quantum cryptography and decentralized security (2021–2026). The results also show increased security complexity due to the integration of advanced technologies and secure architectures with the cloud such as decentralized security (e.g. federated learning also known as distributed AI models), AI driven cybersecurity, zero-trust architectures, privacy-preserving computation and advanced cryptography such as post-quantum cryptography. These technologies are among the most challenging emerging research areas, yet they are the most promising regarding cloud computing. Finally, as cybersecurity technologies evolve, security complexity of the cloud will continue to grow.

Keywords: bibliometric analysis, cloud computing, cybersecurity complexity, cybersecurity evolution, artificial intelligence

1. Introduction

Cloud computing has changed the modern information technology, allowing access to resources including servers, storage, databases, and applications over the internet (Armbrust et al., 2010). This technology offers scalable, flexible, and cost-efficient service models, making it the backbone of digital transformation across different sectors such as healthcare, finance, government and education. According to a report, the global cloud computing market is expected to exceed $1 trillion in 2027 (Gartner, 2023). This shows its significant role in digital economy. However, the migration of business data and operations to cloud environments have created security challenges that demand review of the literature (Hussein, 2021).

Cybersecurity and cloud computing has emerged as important research field in information technology. The multi-tenancy model of cloud services (where multiple users share the same physical infrastructure) can create unique security risks that differ from traditional computing environments (Mell & Grance, 2011). For instance, data breaches, unauthorized access, service disruption, and insider threats represent some of the challenges that researchers and practitioners must address (Alouffi et al., 2021). Furthermore, the rapid evolution of cloud service models such as Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) presents distinct security considerations that require specialized research attention (Khoda Parast et al., 2022). The shared responsibility model in cloud computing also complicates the security responsibilities since both cloud service providers and cloud consumers must manage their security efforts to ensure comprehensive protection (Folorunso et al., 2024).

The literature on cybersecurity of cloud computing has grown gradually over the past decade, replicating the importance of this research area. Early studies focused primarily on identifying and classifying security vulnerabilities inherent in cloud service delivery models (Subashini & Kavitha, 2011; Tabrizchi & Kuchaki, 2020). Other researchers focus on addressing specific technical challenges, including data encryption, access

control mechanisms, intrusion detection systems, and secure computation protocols (Modi et al., 2013; Sun, 2020; Yang et al., 2020; Y. Zhang et al., 2020). More recently, the integration of cloud computing with emerging technologies such as the Internet of Things (IoT), edge computing, blockchain, and artificial intelligence has created new research directions that further increase cybersecurity challenges (Xu et al., 2022; Yang et al., 2020). Multi-cloud and hybrid cloud architectures (mixed environment of cloud and on premises computing) have added additional layers of complexity, requiring unique approaches to security management across hybrid environments (Tabrizchi & Kuchaki Rafsanjani, 2020; Zhang et al., 2020).

Despite the growth of the literature, there is a need for systematic mapping and analysis of this research field to identify research directions and challenges. Bibliometric analysis provides a quantitative methodology for mapping the structure of a research field to identify patterns of growth and knowledge gaps (Chen, 2017; Chen et al., 2023). While several previous studies have studied aspects of cloud computing security, few have provided a bibliometric analysis specifically focused on the complexity of cybersecurity in cloud environments using recent data. This chapter addresses this gap by performing a comprehensive bibliometric analysis of 1,583 publications extracted from Scopus database. This research is guided by the following four research questions:

RQ1: What is the volume and growth of research productivity in the field of cloud computing security?

RQ2: Who are the most productive and influential authors, sources, institutions, and countries, and what is the extent of collaboration in this field?

RQ3: What is the thematic structure of cloud computing security complexities, and how have research themes evolved over time?

RQ4: What are the currently emerging topics, how have the complexities of cloud security evolved, and what potential research trends do the data indicate?

Through bibliometric analysis of literature publications, this study aims to provide a data driven foundation for understanding the current state and future direction of cybersecurity research in cloud computing environments.

This chapter is organized in 7 sections as follows: Section1 provides introduction to this chapter. Section 2 illustrates the theoretical and conceptual background. Section 3 evaluates previous work and compares with this study. Section4 provides the methodology section. Section 5 and section 6 show data analysis, results and discussion. Finally, section 7 demonstrates conclusion and future research directions.

2. Theoretical and Conceptual Background

This section outlines the conceptual foundations across four interconnected domains; cloud computing security, cybersecurity complexity, cloud computing architectures, and emerging security technologies. Then, examines the relationships between these concepts. The aim is to establish a theoretical framework for interpreting bibliometric findings regarding research productivity, collaboration networks, thematic evolution and future research directions.

2.1. Cloud Computing Security

The National Institute of Standards and Technology (NIST) has formally defined cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (Mell & Grance, 2011). This definition highlights five essential characteristics; broad network access, rapid elasticity, measured service, on-demand self-service, and resource pooling. Each of these features carries direct security implications. Given that resources are pooled and accessed via public networks, the trust organizations traditionally placed in defenses are no longer valid (Subashini & Kavitha, 2011).

Subashini and Kavitha (2011) presented one of the first surveys of security issues across the three service delivery models, identifying data confidentiality, integrity, availability, and accountability as the four security pillars in cloud environments. Hashizume et al. (2013) further expanded this classification by identifying seven major threat categories namely; abuse of cloud services, insecure Application Programming Interface (APIs), malicious insiders, vulnerabilities in shared technologies, data loss or leakage, account or service hijacking, and unknown risk profiles. Each establishing differently across IaaS, PaaS, and SaaS deployment models. Subsequent studies confirmed the persistence of these threats and highlighted the expanded attack surface resulting from the uncontrolled nature of hypervisors, multi-tenancy, and the widespread integration of third-party services (Singh & Chatterjee, 2017).

Furthermore, cloud security is not merely a technical issue but also a governance challenge; the loss of physical control over infrastructure undermines traditional assurance mechanisms such as audits, digital forensics, and incident response (Jansen, 2011). A fundamental challenge identified in this literature is the need to balance the economic benefits of resource sharing against the requirements for protecting workloads that were not originally designed for shared infrastructure (Zhang et al., 2010).

2.2. Cybersecurity Complexity

Cybersecurity is defined as a complex socio-technical problem in which technological tools, human elements, organizational processes, and regulatory systems interact in non-linear and often unpredictable ways (Bodeau et al., 2011; Soomro et al., 2016). This complexity arises not only from the increasing sophisticated cyber-attacks methods but also from the diversity of systems requiring protection, the speed at which security vulnerabilities are discovered, and the costs of attacks versus defenses. Unlike physical security, cybersecurity requires defenders to maintain constant awareness of vulnerabilities across various attack surfaces, whereas attackers need to succeed only once (National Institute of Standards and Technology, 2018).

Bodeau et al. (2011) introduced the concept of cyber resilience to emphasize that prevention alone is insufficient, and organizations should assume that a breach will occur and design their systems to withstand, respond to, and recover from it. This perspective reframes security as an emergent property of system design rather than merely a checklist of controls. The NIST cybersecurity framework operationalizes this perspective through its five functions (Identify, Protect, Detect, Respond, and Recover) with each function addressing a different level of complexity (Barrett, 2018). The framework acknowledges that threats evolve faster than controls can be adopted and it prioritizes continuous improvement and risk-based decision making over static compliance.

Soomro et al. (2016) emphasized the human and managerial dimensions of this complexity, noting that the majority of security failures from inadequate training or governance gaps rather than technical vulnerabilities. The spread of regulation such as the EU's General Data Protection Regulation (GDPR), the Health Insurance Portability and Accountability Act (HIPAA), the Payment Card Industry Data Security Standard (PCI DSS), and other sector specific national laws increase the issue. By fragmenting the compliance that cloud computing operators must navigate. Specifically, within the context of cloud computing, the stakeholders (providers, tenants, brokers, auditors, and regulators) creates interdependencies where in a single configuration error can spread across organizational boundaries (Hashizume et al., 2013).

2.3. Cloud Computing Architectures

Cloud computing architectures are traditionally classified into two dimensions: the service model and the deployment model. The service model dimension distinguishes between infrastructure as a service, platform as a service, and software as a service. Each defines a different level of abstraction through which the provider grants the customer access to resources (Mell & Grance, 2011; Zhang et al., 2010). The deployment model dimension distinguishes between public, private, and hybrid clouds, which differ based on the entity that owns, manages, and accesses the underlying infrastructure. Together, these dimensions form a design space

in which security responsibilities shift fundamentally: an IaaS customer retains control at the operating system level thereby bearing the bulk of the security burden whereas a SaaS customer delegates almost all security responsibilities to the provider, effectively inheriting the provider security posture (Rittinghouse & Ransome, 2010; Subashini & Kavitha, 2011).

Marston et al. in (2011) contextualized cloud computing architecture within the business, noting that the architectural choices made by organizations are driven less by technical efficiency than by cost, risk exposure, and the strategic value of the workloads being migrated. Wang et al. (2008) presented one of the earliest academic perspectives on cloud computing architecture, describing it as a combination of utility computing, distributed systems, and virtualization technologies. The virtualization layer typically implemented via hypervisors or container runtime environments is the architectural component that enables flexibility; however, it also represents the most critical attack surface as a single vulnerability in the hypervisor can compromise all virtual machines running on the host (Hashizume et al., 2013).

Modern cloud computing architectures have evolved from virtual machines to microservices, serverless functions, and container orchestration platforms such as Kubernetes. Shi et al. (2016), this architectural scope expanded to include the network edge, due to the rise of edge cloud computing architectures that place computing resources closer to data sources. This approach aims to reduce latency and bandwidth costs while raising new questions regarding physical security and trust. These architectural developments are not security neutral since each new layer of abstraction enhances the architectures of the cloud and also increases the number of components requiring hardening, monitoring, and updating thereby increasing the cybersecurity complexities.

2.4. Emerging Security Technologies

In response to architectural threats, a wave of emerging security technologies has surfaced, with machine learning and artificial intelligence gathering the most attention. Artificial intelligence and Machine Learning (ML) have emerged as security technologies for cloud environments, addressing the shortcomings of traditional, static, rule-based systems when facing dynamic attacks (Alzoubi et al., 2024). By leveraging automated pattern recognition, behavioral analytics, and predictive modeling, these technologies enhance capabilities for threat detection, access management, and security incident response across complex cloud architectures (Babaei et al., 2023).

Decentralized models are transforming how cloud computing models are trained, particularly through Federated Learning (FL); Algorithms are trained across edge devices and distributed servers without the need to transfer raw, private data to a central location (Albshaier et al., 2025; Devarapalem, 2025). Systematic reviews indicate that federated learning reduces privacy risks by 25% in sensitive domains and enhances threat detection capabilities by 40% within critical infrastructure, although 50% of implementation cases highlight challenges related to communication latency (Albshaier et al., 2025).

Despite this potential, several operational and technical vulnerabilities hinder the technology's widespread adoption. Susceptibility to adversarial machine learning attacks allows attackers to manipulate input data to poison training models or evade detection.

Furthermore, high computational overhead and latency make real-time model retraining a costly and resource-intensive process in multi-tenant systems (Sarraf & Pal, 2025). Furthermore, the lack of model interpretability and explainability undermines trust and the feasibility of regulatory auditing regarding automated cloud defense mechanisms (Alzoubi et al., 2024; Sarraf & Pal, 2025). Finally, data privacy requirements impose complexities on large scale training processes that necessitate massive behavioral datasets (Alzoubi et al., 2024).

Blockchain and distributed ledger technologies have been proposed as mechanisms to enhance the integrity, auditability, and decentralization of cloud computing security controls. A 2019 study examined the intersection of blockchain and artificial intelligence within cloud computing environments, identifying applications such as decentralized identity, tamper-resistant data logging, and verifiable computing (Salah et al., 2019). However, a study by Kolb et al. (2020) indicated that data transfer rates, latency, and energy consumption in public blockchains limit their applicability to specific scenario such as audit logs and supply chain tracking rather than general-purpose cloud computing security.

The Zero Trust architecture has emerged as a shift from a static based defense to the continuous verification of identity for every request. NIST Special Publication 800-207 established the Zero Trust concept as a set of logical components of policy engine, policy administrator, and policy enforcement point operating independently of network location (Rose et al., 2020). This model is highly suitable for cloud computing architectures, as it treats every interaction as untrusted, aligning naturally with the distributed and multi-tenant nature of cloud workloads.

Advancements in cryptography have led to the emergence of two additional sets of technologies. Fully homomorphic encryption enables computations to be performed on ciphertext without the need for decryption, promising the potential for fully confidential data processing on untrusted cloud infrastructure, although performance costs remain a barrier to widespread adoption (Armknecht et al., 2015). Post-quantum cryptography is being developed to handle the cryptographic breaches that large scale quantum computers will inflict upon encryption algorithms (Mosca, 2018).

2.5. Relationships Among the Main Concepts

The four concepts reviewed in this section are not independent research field rather, they form a tightly interconnected conceptual system. Cloud architectures define the structural attack surface: the choice of service model determines what the client can control, and the deployment

model choice determines which entities share the underlying infrastructure, while the architectural pattern (whether microservices, serverless, or edge computing) defines the pathways or touchpoints through which security vulnerabilities propagate. Cybersecurity complexity is a systemic condition arising from these architectural choices when exposed to diverse threat actors and varying regulatory frameworks; in other words, complexity is the product of architecture in the presence of adversaries.

Conversely, emerging security technologies represent responses developed by the research community to address specific facets of complexity within particular architectural configurations. The zero-trust principle emerged in response to the traditional network boundaries caused by cloud native architectures; "Confidential Computing" offers a solution to the inability of traditional encryption to protect data during processing; and machine learning-based detection technologies handle vast amounts of telemetry data that exceed human analytical capacity. Blockchain technology addresses the trust gaps among multiple parties that arise when cloud services are deployed across different organizations (Rose et al., 2020; Tabrizchi & Kuchaki Rafsanjani, 2020). However, each emerging technology brings its own new complexities. Machine learning models are vulnerable to attacks via adversarial examples and data poisoning. Isolated confidential computing environments remain susceptible to side-channel attacks. Blockchains present challenges regarding key management and scalability and the transition to quantum-resistant encryption systems (post-quantum migration) requires comprehensive coordination across entire cryptographic ecosystems (Buczak & Guven, 2016; Mosca, 2018). These defensive technologies become sources of new risks is precisely why bibliometric studies treat cloud computing security as an evolving, ongoing issue rather than a definitively resolved one.

3. Related Work

The evolution of cloud computing highlights a shift from traditional infrastructure concerns to multi-dimensional security challenges (Abdulle et al., 2026; Cai et al., 2015). Early bibliometric assessments identified security as active research area along with virtualization and distributed computing (Cai et al., 2015). Later analyses observing an average 15% annual increase in publications related to cloud security between 2010 and 2018 (Thiam et al., 2019). Despite this growth, recent studies indicate a persistent gap between published research and real-world challenges as nine out of ten security professionals are concerned about cloud security (Garg et al., 2019).

Recent research has increasingly focused on the role of advanced computational techniques (such as AI based detection and prevention techniques) in managing cloud threats and its architecture complexity (Alzoubi et al., 2024). Several studies have identified 2018 as a key year where AI cybersecurity research accelerated due to the availability of deep learning frameworks and datasets (Chuang & Chuang, 2026). Machine learning and deep learning models have also shown major effect in identifying and mitigating cloud security threats through anomaly detection and prevention systems and security automation (Alzoubi et al., 2024).

Beyond technical detection, some scholars have also examined specific security mechanisms and their socio-economic effects (Abdulle et al., 2026; Reddy et al., 2026). Scient metric analyses targeting access control and encryption techniques reveal research clusters in federated learning and post-quantum cryptography (Dayyabu et al., 2020). From an economic point of view, security is no longer just a technical requirement but a major cost factor effecting organizational adoption and investment decisions (Abdulle et al., 2026).

However, the complexity of cloud architecture introduces unique threats and uncertainties. Risks and uncertainties arise from supply chain stability such as outsourcing and vendor maturity, noting that the

complexity of interconnected systems of systems significantly increases the possibility of failure (Zied Milian et al., 2017). Cloud native systems (composed of containers and microservices communicating through distributed networks) present complex security risks that conventional countermeasures struggle to monitor (Chuang & Chuang, 2026). This complexity is further expanded by IoT devices integration which significantly increases the attack surface (Garg et al., 2019; Thiam et al., 2019).

While existing bibliometric studies have provided valuable overviews, the present study addresses this gap by studying cybersecurity complexity inherent in modern cloud environments. While existing sources provide high-level scientific mapping of the field, the present study addresses this gap by examining how cybersecurity complexity has evolved and how it creates a level of complexity that traditional defense mechanisms struggle to mitigate. Table 1 provides a comparison with related previous studies in the literature.

Table 1. A comparison with related previous studies in the literature

Paper	Focus Area	Methodology	Key Findings	Complexity Outlook
Abdulle et al., 2026	Cost-Benefit Analysis (CBA)	Bibliometric (Scopus)	Security is considered an emerging cost factor when adopting cloud computing.	Complexity arises from new cloud models like edge and serverless.
Alzoubi et al., 2024	ML & DL for cloud security	Bibliometric (Scopus)	Focus on anomaly detection, automation, and privacy.	Security addressed through neural network architectures
Thiam et al., 2019	Rise of cloud security (2010-2018)	Bibliometric (WoS)	15% annual growth; China, India, USA are top contributors.	Complexity mentioned regarding IoT and increased attack surfaces.
Cai et al., 2015	General cloud computing	Bibliometric (SCI-E, etc.)	Security is a top 5 research topic; mobile cloud is a future hotspot.	Identifies non-functional complexity: elasticity and adaptability.
Chuang & Chuang, 2026	Global cyber-attack trends	Bibliometric	Shift from reactive proactive AI-driven counter measues.	Cybersecurity is an interdisciplinary challenge with legal angles.
Dayyabu et al., 2020	Cloud security research	Bibliometric (Scopus)	IaaS is the most researched model; access control is a major gap.	Complexity in multi-tenancy and virtualization nature.

Garg et al., 2019	Emerging security trends	Bibliometric (Scopus)	Gap between research and industry.	Complexity in trust management and IoT integration.
Judijanto & Vandika, 2026	Cloud-native security	Bibliometric	Move toward DevSecOps, Kubernetes, and AI-driven models.	Complexity in temporary containers and distributed networks.
Reddy et al., 2026	Access control & encryption	Scientometric	blockchain security and post-quantum cryptography trends.	Fragmentation between technical factors and legal frameworks.
Zied Milian et al., 2017	Risks and uncertainties	Systematic review	Risks originate from vendor maturity and supply chain deliveries.	Addresses complexity of systems of systems'.
This study	Cybersecurity complexity and emerging research area	Bibliometric analysis (Scopus)	Analyzes the complex technological advancement	Complexity as the primary driver of modern vulnerabilities.

4. Research Methodology

4.1 Data Collection and Search Strategy

The data in this bibliometric analysis was extracted from Scopus database, which is one of the largest databases of peer-reviewed papers. The search query was designed to capture publications of cybersecurity and cloud computing. The search was conducted in August 2026, and the results were limited to English-language documents published between 2010 and 2026 to maintain consistency and relevance. The initial search generated a comprehensive set of papers, which was refined through a systematic filtering process (highlighted in figure1) to ensure the relevance and quality of the dataset.

The inclusion criteria required that papers be indexed in Scopus, published between 2010 and August 2026 (10 of August 2026 date of extracting the dataset which reflect almost 3 quarters of the year), written in English, and directly address topics related to cybersecurity in cloud computing. Both peer reviewed research articles and review papers were included to cover the literature. Conference papers, book chapters, and other non-journal document types were excluded to maintain consistency.

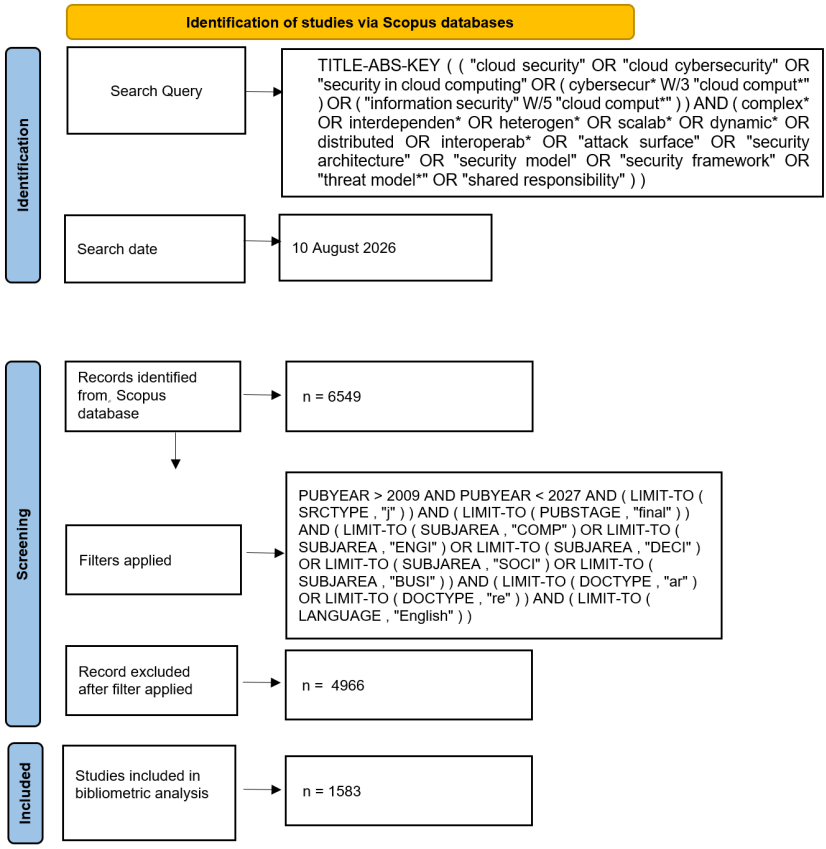


Figure 1. Search query, filtering, inclusion and exclusion mechanism

The final dataset (as shown in figure 2) includes 1,583 publications, including 1,488 research articles (94.0%) and 95 review papers (6.0%). This database provides a solid basis for performing bibliometric analysis that reflects the progress of research in this field.

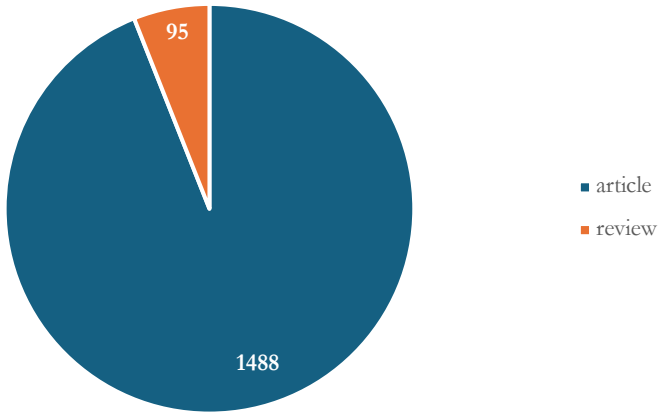


Figure 2. Distribution of papers containing 1,488 articles and 95 review papers

4.2. Analytical Framework

The bibliometric analysis was conducted using an analytical framework that included seven key dimensions:

1. Time-based publication trends analysis to identify growth patterns including calculating Compound Annual Growth Rates (CAGR).
2. Journal productivity analysis and Bradford's Law assessment to evaluate primary publisher and literature spreading across journals.
3. Author productivity analysis and Lotka's Law examination to understand the distribution of scientific output among researchers.
4. Geographical distribution analysis to map the global research at country and institutional levels.
5. Citation analysis, including total citations, average citations per paper, h-index calculation, and identification of the most cited papers.
6. Keyword frequency analysis, co-occurrence mapping, and tracking temporal subject development across three time periods.
7. International research collaboration analysis by creating a country-level collaboration heat map.

The graphs were created using Biblioshiny and Microsoft Excel to produce the results of various graphical formats, such as bar charts, pie charts, and heat maps. All data processing and analysis were performed using Bibliomtrix (Biblioshiny package within RStudio version 2026.05.1, build 225) to ensure reproducibility and minimize human error. Furthermore, the research based on questions ensures that each part of the analysis directly addresses one or more of the four research questions guiding this study.

5. Results and Analysis

5.1 Publication Volume and Growth Dynamics (RQ1)

The distribution of publications provides a comprehensive overview of the research progress and maturity of the field. As illustrated in Figure 3 and Table 2, the annual output of papers shows a sustained upward trend from 2010 to 2026. The earliest publications in the dataset date back to 2010, with only three publications recorded that year, reflecting the field's initial phase. This period coincides with the publication of the NIST definition of cloud computing, which provides a standardized framework for both industrial adoption and academic research. The field experienced a significant turning point between 2014 and 2015, with annual output increasing from 24 publications in 2014 to 43 in 2015, representing a yearly growth of 79.2%, indicating the beginning of academic interest in cloud computing security.

In 2015, this field experienced rapid growth. Annual output rose from 50 publications in 2016 to 96 in 2019, before temporarily declining to 73 in 2020. The post pandemic recovery was remarkably strong, with output increasing from 78 publications in 2021 to 156 in 2022 (a 100% increase) representing the largest year growth in the data. Growth then accelerated to 212 publications in 2024 and 358 in 2025. 2026 so far shows 202 publications, and this number is expected to rise as more papers are indexed. The line in Figure 3 highlights a steady growth of this field.

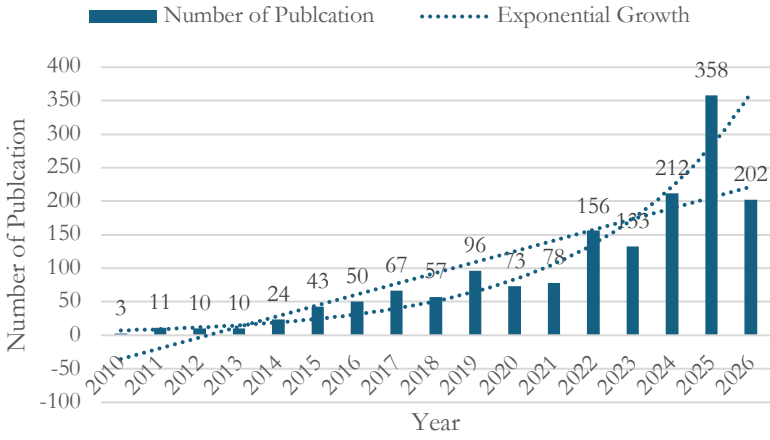


Figure 3. Annual publication trend in cloud computing cybersecurity research (2010-2026), shows steady exponential growth with a polynomial trend

Table 2. Annual distribution of publications in the field of cybersecurity for cloud computing (2010-2026)

Year	Publications	Percentage
2010	3	0.19%
2011	11	0.69%
2012	10	0.63%
2013	10	0.63%
2014	24	1.52%
2015	43	2.72%
2016	50	3.16%
2017	67	4.23%
2018	57	3.60%
2019	96	6.06%
2020	73	4.61%
2021	78	4.93%
2022	156	9.85%
2023	133	8.40%
2024	212	13.39%
2025	358	22.62%
2026	202	12.76%
Total	1,583	100.00%

5.2. Most Productive and Impactful Sources (RQ2)

Journal productivity analysis reveals the key publishing platforms shaping the cloud computing cybersecurity. As illustrated in Figure 4 and Table 3, Institute of Electrical and Electronics Engineers (IEEE Access) dominates with 74 publications (4.67% of total output), followed by Cluster Computing (38 publications, 2.40%), IEEE Transactions on Cloud Computing (37 publications, 2.34%), IEEE Transactions on Dependable and Secure Computing (32 publications, 2.02%) and the International Journal of Advanced Computer Science and Applications (30 publications, 1.90%). These five journals collectively account for 211 publications (13.33% of the total), indicating a medium level of focus on this field.

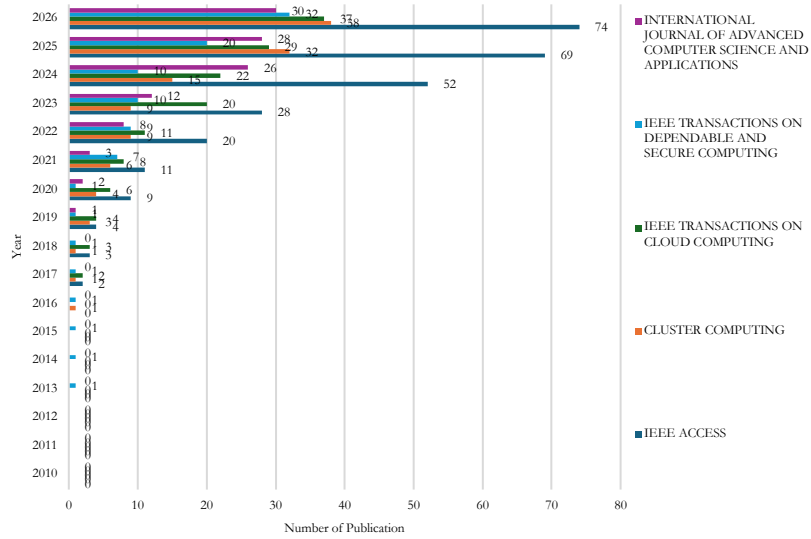


Figure 4. Productive journals in the field of cybersecurity research for cloud computing

Table 3. Top 15 journals in terms of productivity, number of publications, and citation impact

Rank	Journal	Papers	Total Cit.
1	IEEE Access	74	1,755
2	Cluster Computing	38	633
3	IEEE Trans. Cloud Computing	37	796
4	IEEE Trans. Dependable and Secure Computing	32	652
5	Int'l J. Adv. Comput. Sci. Appl.	30	N/A
6	Journal of Cloud Computing	28	801
7	J. Theoretical and Applied Info. Tech.	27	N/A
8	Computers and Security	25	N/A
9	IEEE Trans. Info. Forensics and Security	22	N/A
10	IEEE Trans. Services Computing	21	731
11	Future Generation Computer Systems	20	827
12	IEEE Internet of Things Journal	19	527
13	Applied Sciences (Switzerland)	19	N/A
14	Computers, Materials and Continua	18	N/A
15	Sensors	18	541

Analyzing the journal distribution using Bradford law (Brookes, 1985) reveals a three-region structure. As shown in figure 5, region 1 (the core) comprises 22 journals that contributed approximately 533 articles (one-third of the total), while region 2 contains 86 journals that contributed an additional 528 articles, and region 3 consists of 372 that contributed the remaining 522 articles. Bradford multiplier of 4.12 is slightly higher than the theoretical value of approximately 3.0, representing a moderate concentration of publications in the core journals. This distribution pattern is consistent with a stable publishing environment and a mature research field.

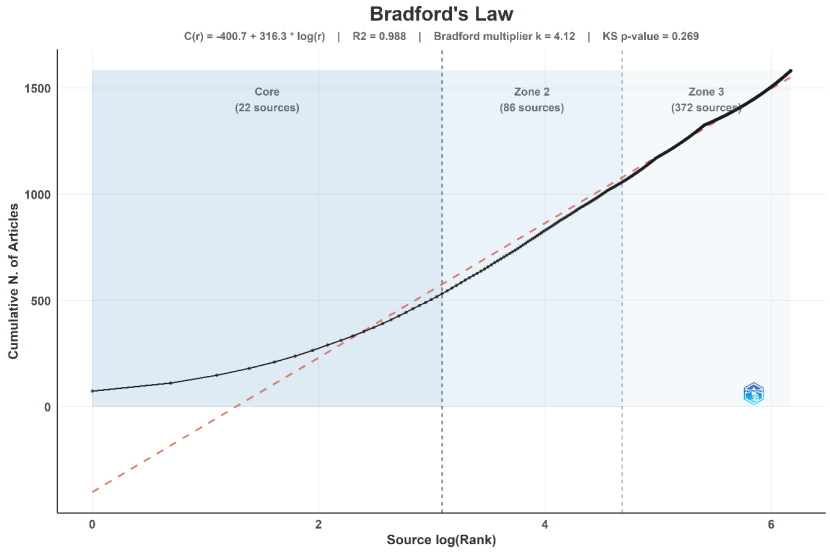


Figure 5. Core sources by Bradford's law

When considering the impact of citations rather than simply the volume of publications, the ranking changes significantly, as illustrated in figure 6. The journal Network and Computer Applications in the top of the list with a total of 3,087 citations from just 13 papers (an average of 237.5 citations per paper), followed by IEEE Access with 1,755 citations, then IEEE Communications Surveys and Tutorials (1,030 citations from 3 papers, an average of 343.3 citations per paper), and finally Future Generation Computer Systems (827 citations from 20 papers). Journal IEICE Transactions on Communications contributed a single paper that gathered 701 citations, demonstrating how a highly piece of work can significantly increase a journal citation count. These findings confirm the importance of considering quantitative and qualitative indicators when evaluating the publishing environment within a research field.

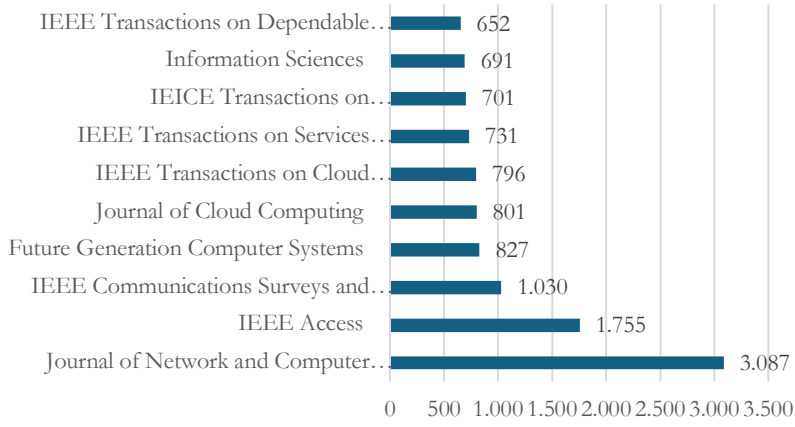


Figure 6. The top 10 journals ranked by total citations

5.3. Productive and Impactful Authors and Institutions (RQ2)

Analysis of author productivity reveals a highly skewed distribution consistent with Lotka's law of scientific productivity, which states that a small number of authors produce the majority of publications (Lotka, 1926). The most common authors in the dataset are from India and China origin based on the affiliation data, reflecting the geographic distribution of research output. Although the difference is small, the data show that the most common author country origin collectively represents a significant portion of total published output, with a steady research activity spanning 8 to 15 years. This pattern suggests the presence of specialized research groups and a long-term scientific commitment to this domain knowledge. As shown in figure 7 the distribution of productivity among authors follows an inverse squared approximation consistent with Lotka's classical formulation, where the number of authors publishing n papers is approximately proportional to $1/n^2$.

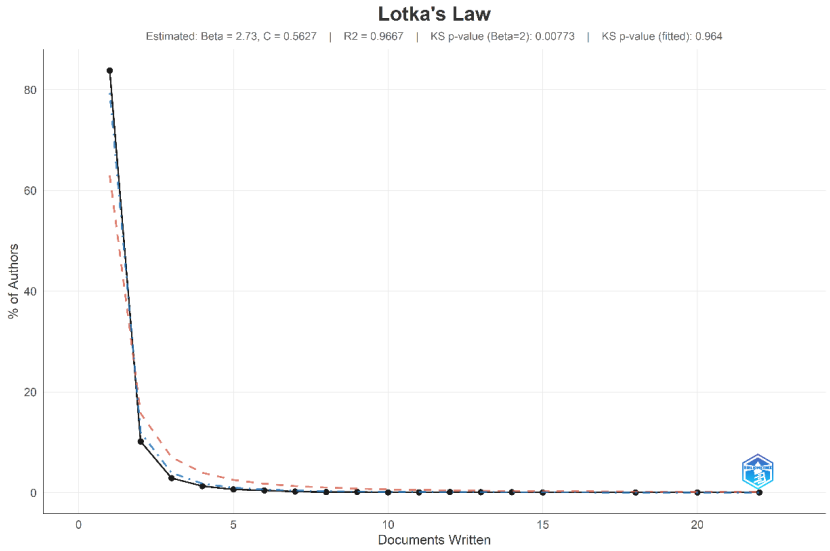


Figure 7. Author Productivity through Lotka's Law

The institutional analysis, illustrated in figure 8, shows that the most productive partnerships are mainly with Indian and Chinese universities. India's National Institutes of Technology (NIT) system leads the list with 35 partnerships, followed by Vellore Institute of Technology (25), Beijing University of Posts and Telecommunications (22), Xi'an Electronic University (22), and Anna University (22). These five institutions collectively form 126 partnerships, reflecting the concentration of research investment in cloud computing security at these universities. The strong performance of Indian institutions aligns with India's position as a leading data producer. Notably, King Abdulaziz University of Saudi Arabia appears among the top institutions, reflecting the Kingdom's increasing investment in cybersecurity research. The presence of Nanyang Technological University (Singapore) and the University of Melbourne (Australia) in the top 15 also demonstrates the research contributions of high-quality institutions outside the dominant India-China association. In terms of productive authors in the literature, figure 9 shows the top 10 most productive authors.

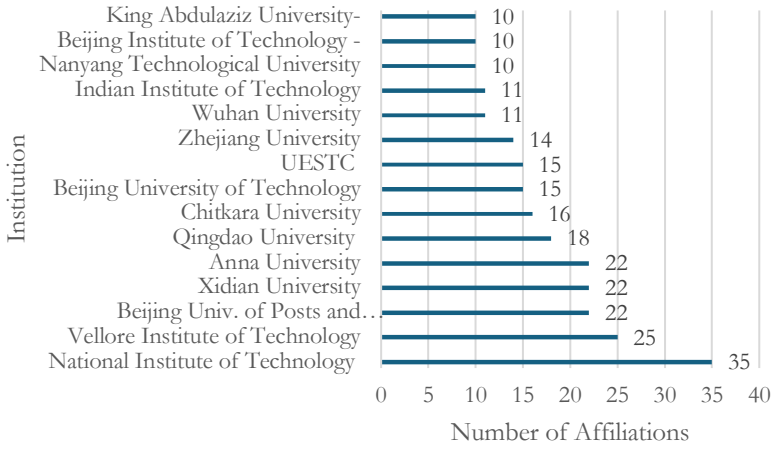


Figure 8. Top 15 productive institutions contributing to this field

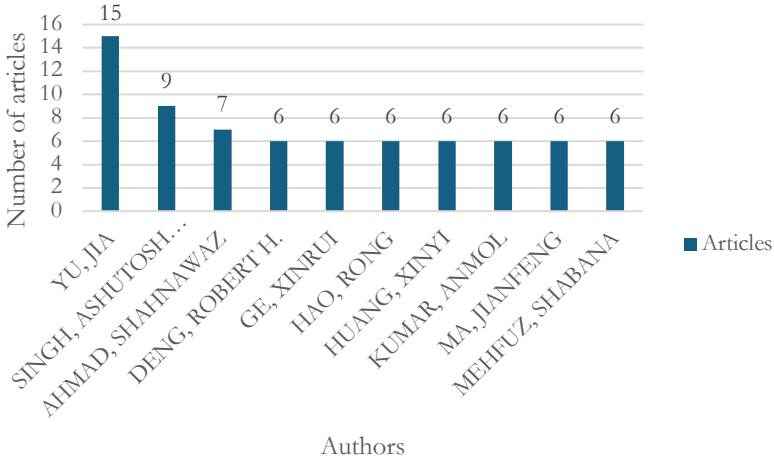


Figure 9. Most productive author

5.4. Geographic Distribution of Research (RQ2)

The geographical distribution of research production (as illustrated in figure 10) reveals a global concentration dominated by Asian countries. India leads the field with 619 affiliations (representing the largest share of total output), followed by China with 397. Together, these two countries account for over 64% of global research productivity in cloud computing

cybersecurity. This reflects their investments in higher education research, government funding, and rapid digital transformation of the economies. The US ranks third with 149 affiliations, followed by Saudi Arabia 130, the UK 87, Australia 66, and South Korea 53 affiliations.

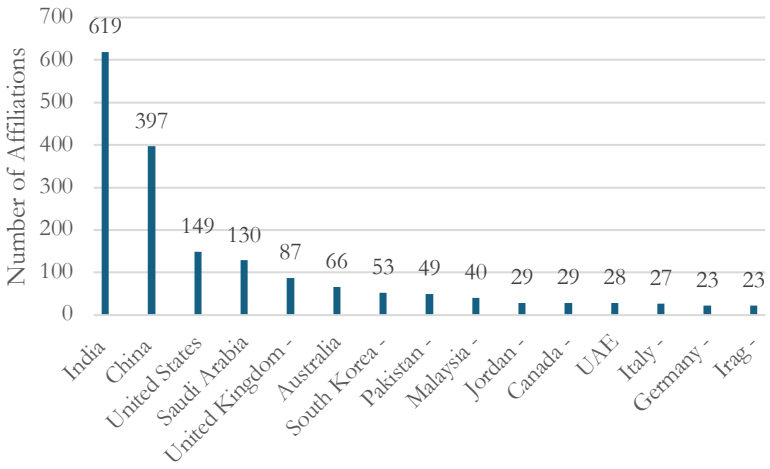


Figure 10. The top 15 countries/regions in terms of their affiliations in the field of cyber knowledge for cloud computing

The dominance of India and China can be accredited to several factors. First, both countries have implemented national strategies for cloud computing and cybersecurity, stimulating academic research in these areas. The cybersecurity policy of India and cybersecurity law of China have contributed to forming regulatory frameworks that demand more cybersecurity research (Mukhopadhyay, 2022; Sevenard, 2026). Second, the rapid growth of their IT sectors and the increasing adoption of cloud computing services across all sectors may have created strong demand for cybersecurity research. Third, both countries have large academic communities with a strong publishing culture, and their researchers regularly publish in open-access journals and IEEE journals that dominate the field (Feng & Garg, 2021). Saudi Arabia presence among the top five reflects its Vision 2030 program, which has funded numerous cybersecurity research centers and international joint ventures (Hussain, 2026). The low representation of African and Latin American countries

might indicate potential gaps in global research capabilities in cybersecurity, which requires attention.

5.5. Citation Analysis and Scholarly Impact (RQ2)

Citation analysis provides a quantitative measure of the scientific influence of research productions in specific field. The dataset accumulated 29,322 citations (average 18.52 citations per publication) with a median of 4.0 citations. The h-index for the dataset was 76, meaning that 76 research papers each received at least 76 citations. This significant value places the research area among the most influential in computer science. While this index is lower than those of more established fields, it is still notable given the field's relatively progressing.

As illustrated in Figure 11, the distribution of citations follows a highly skewed pattern which is common pattern in scientific literature. 333 publications (21.04%) remained uncited which is a moderate percentage compared to broader scientific fields. suggest that research in this area tends to gain traction over time. The largest group, (comprising 540 publications (34.11%) each received between one and five citations, followed by 243 publications (15.35%) with between 11 and 25 citations. Notably, 45 publications (2.84%) composed over 100 citations each which represents the highly influential core of the field. Only one publication exceeded 1,000 citations, highlighting the field reliance on a limited number of works that shaped its theoretical foundations.

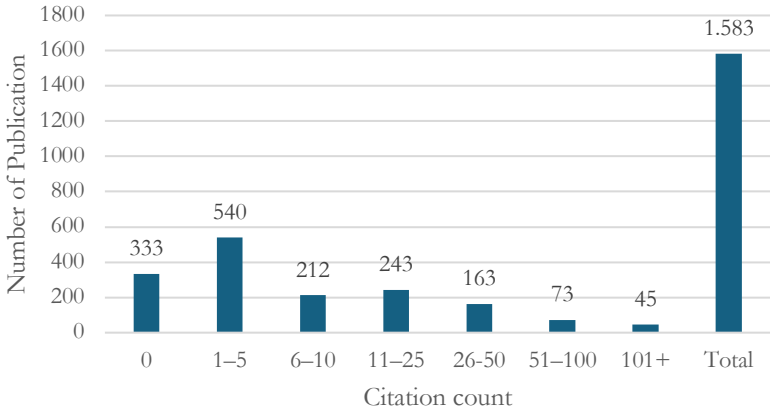


Figure 11. The distribution of publications by number of citations

The most cited study in the dataset shown in figure 12 and table 4 is Subashini and Kavitha's 2011 influential study on security issues in cloud computing service delivery models (Subashini & Kavitha, 2011). The paper collected 2,138 citations and is considered as a foundational reference in the field. This is followed by Stoyanova et al.'s comprehensive 2020 study on IoT forensics, which received 797 citations (Stoyanova et al., 2020). Fu et al.'s influential 2015 study on achieving effective cloud search services (Fu et al., 2015) received 701 citations. These highly cited studies represent the theoretical foundations which much of the subsequent research addressing fundamental challenges in cloud security such as IoT integration privacy preserving and cryptography. The range of publisher presenting the most cited papers such as ACM to IEEE and Elsevier publications giving the indication that influential publication is spread across the publishing environment rather than concentrated in a single publisher.

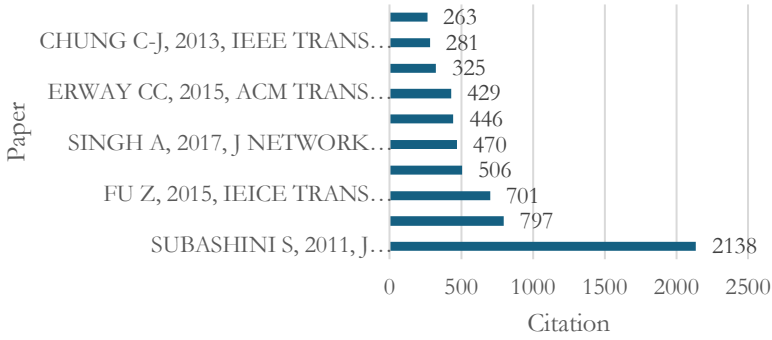


Figure 12. Most cited research papers in the dataset with authors and year, which represent foundational and highly influential works

Table 4. Most cited research papers in the dataset, which represent foundational and highly influential works

Paper	Total Citations
SUBASHINI S, 2011, J NETWORK COMPUT APPL	2138
STOYANOVA M, 2020, IEEE COMMUN SURV TUTOR	797
FU Z, 2015, IEICE TRANS COMMUN	701
ZHAO C, 2019, INF SCI	506
SINGH A, 2017, J NETWORK COMPUT APPL	470
YANG H, 2019, IISE TRANS	446
ERWAY CC, 2015, ACM TRANS INF SYST SECUR	429
BAUMANN A, 2015, ACM TRANS COMPUT SYST	325
CHUNG C-J, 2013, IEEE TRANS DEPENDABLE SECURE COMPUT	281
SHIRAZI SN, 2017, IEEE J SEL AREAS COMMUN	263

5.6 Thematic Structure and Evolution (RQ3)

Keyword analysis provides authors with a frame into the field structure and evolution. As illustrated in Figure 13, Figure 14, Figure 15 and Table 5, the most frequent occurring keywords are: cloud computing security (524 times), cloud computing (501 times), security (153 times), blockchain technology (77 times), machine learning (68 times), data security (67 times), cloud storage (59 times), encryption (57 times), and deep learning (57 times). The close alignment of cloud computing security and cloud computing as the two most common keywords highlights that this dataset effectively covers the intersection of these two fields. The

strong presence of blockchain technology, machine learning, and deep learning among the most frequent keywords also indicates the growing combination of emerging technologies with cloud computing security research.

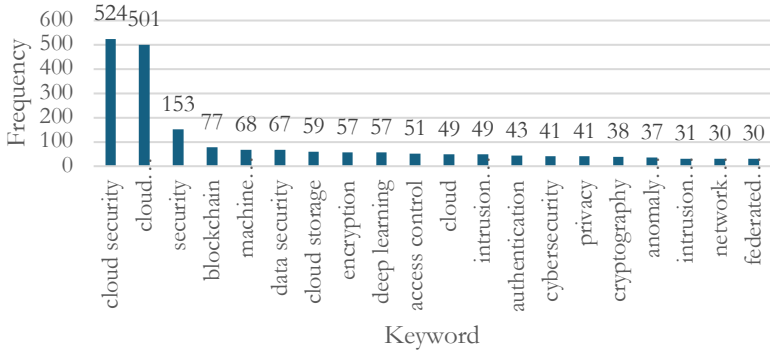


Figure 13. Top 20 author keywords, illustrating the thematic composition and research priorities within the field

Table 5. Author keywords ranked by frequency of occurrence

Rank	Keyword	Freq.
1	cloud security	524
2	cloud computing	501
3	security	153
4	blockchain	77
5	machine learning	68
6	data security	67
7	cloud storage	59
8	encryption	57
9	deep learning	57
10	access control	51
11	cloud	49
12	intrusion detection	49
13	authentication	43
14	cybersecurity	41
15	privacy	41
16	cryptography	38
17	anomaly detection	37
18	intrusion detection system	31
19	network security	30
20	federated learning	30

Keyword analysis reveals a clear three-stage thematic evolution, as illustrated in Figure 14. In the foundational stage (2010–2015), research focused mainly on core cloud computing security concepts, with prominent keywords such as cloud computing (56 times), cloud computing security (44 times), and security (12 times). This period was categorized by concentrated efforts to identify and address the fundamental security vulnerabilities in cloud computing service delivery models. The emergence of virtualization and SaaS models as top keywords reflects the technical focus of this early period.

The evolution stage (2016–2020) saw a widen of the research topics, with cloud computing security (216 times) and cloud computing (169 times) remaining dominant. Emerged topics such encryption (22 times), Distributed Denial-of-Service (DDoS) attacks (11 times), cloud storage (15 times), and privacy (11 times). The emergence of distributed denial-of-service attacks as a key term reflects growing concerns about these attacks targeting cloud infrastructure. The rise of privacy concerns also indicates a growing awareness of data protection challenges. This phase occurred with the rapid increase of cloud computing services across different sectors, accompanied by an expansion in the scope of threats.

The final phase (2021-2026) is categorized by the significant rise of AI-powered security and blockchain technology. The use of blockchain term increased 77 times while machine learning 68 times, deep learning 57 times, and federated learning 30 times. This phase represents a major shift toward intelligent, data driven security solutions that utilize advanced computing technologies. For example, utilization of AI models for detection, prevention, and response countermeasures to sophisticated cyber threats. Analysis of co-occurrence reveals strong thematic links, with the most prominent keyword pairs being cloud computing - cloud computing security (118 times), cloud computing - security (76 times), cloud computing - data security (34 times), and cloud computing security - machine learning (28 times), indicating the emergence of integrated research of multiple technology fields.

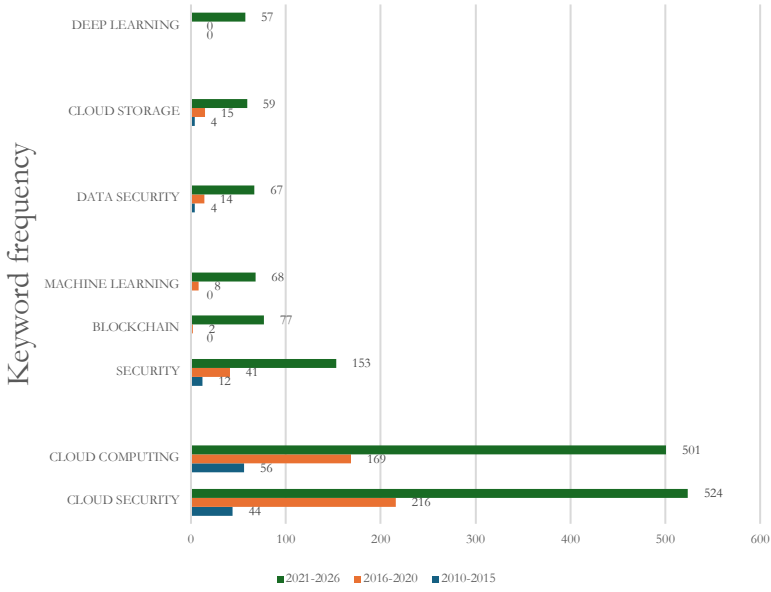


Figure 14. Thematic evolution of research keywords across three time periods (2010–2015, 2016–2020, 2021–2026).

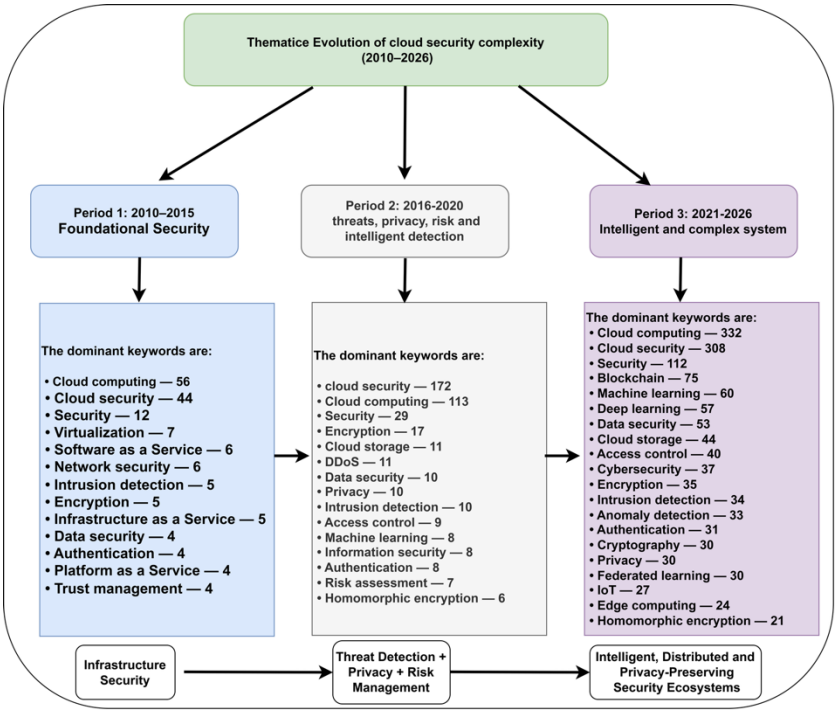


Figure 15. Thematic evolution of cloud security complexity and dominant keywords for each period

5.7. International Research Collaboration (RQ4)

The analysis of international research collaboration patterns provides insights into the global knowledge exchange network within this field. Among the 1,583 papers analyzed, 424 (26.84%) involved international collaborations between scholars from two or more countries whereas 1,156 publications (73.16%) originated from a single country. 3 records had no identified country in affiliation field. This suggests that while majority of research is conducted within national borders, a significant and growing percentage involves cross border partnerships. The relatively moderate rate of collaboration also indicates that this field has not yet reached the level of internationalization seen in more mature research areas, such as climate science, where international partnerships rates typically exceed 40%.

The heatmap in Table 6 illustrates the density and structure of international research cooperation among the ten most productive countries. The strongest collaborative links are between China and the United States (33 joint publications), Saudi Arabia and India (23), China and Australia (26), Saudi Arabia and Pakistan (19), and China and the United Kingdom (16). China's central position in the collaborative network reflects its dual role as a major producer of research and an active partner with institutions in Asia, North America, Europe. The strong links between Saudi Arabia and Pakistan, and between Saudi Arabia and India reflect Saudi Arabia's active investment in international research cooperation, particularly through scholarship programs that attract researchers from South Asian countries (Polizzi, 2026). The China-US collaboration is particularly important, bringing together the two largest economies and their strengths in cloud computing and cybersecurity research.

Table 6. Heat map of international cooperation showing the frequency of joint publications among the ten most productive countries

	China	**Saudi Arabia**	**India**	**USA**	**UK**	**Australia**	**Pakistan**	**Malaysia**	**UAE**	**Jordan**
China	0	16	14	33	16	26	11	6	2	2
Saudi Arabia	16	0	23	10	15	4	19	9	8	11
India	14	23	0	13	10	7	3	9	2	2
USA	33	10	13	0	6	3	2	4	4	1
United Kingdom	16	15	10	6	0	9	7	4	2	3
Australia	26	4	7	3	9	0	1	0	2	2
Pakistan	11	19	3	2	7	1	0	7	6	2
Malaysia	6	9	9	4	4	0	7	0	1	0
UAE	2	8	2	4	2	2	6	1	0	4
Jordan	2	11	2	1	3	2	2	0	4	0

The publisher analysis, shown in Figure 16, reveals the dominance of the IEEE institution in the publishing market with 290 publications, followed by Springer (211), Elsevier (184), and finally MDPI (100). IEEE dominance aligns with the field's strong focus on engineering and applied computer science. The combined output of the top five publishers

represents over 40% of total production, indicating a medium level of publisher focus. MDPI's presence reflects growing trend toward open access publishing which impacts the accessibility of research findings.

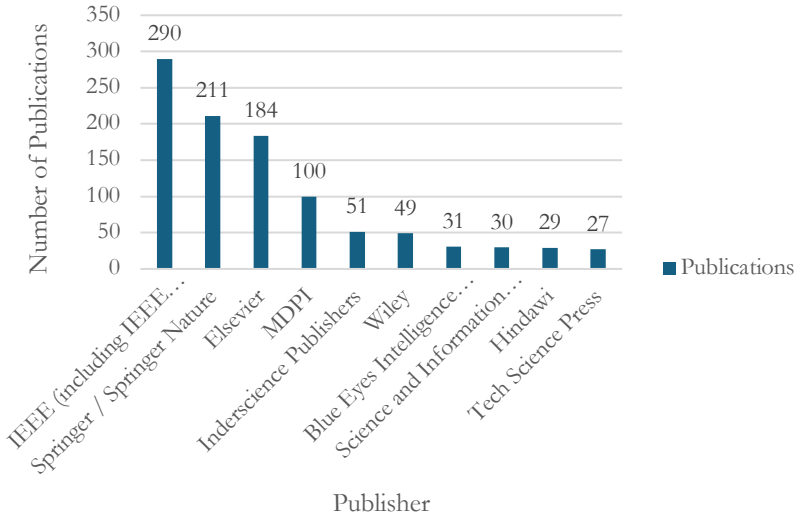


Figure 16. The top 10 publishers by publication volume, demonstrating the dominance of IEEE and Springer in this research field

6. Discussion

6.1. Analysis of Key Findings

The discussion chapter evaluates the growth, intellectual structure, and thematic shifts in research concerning the complexities of cloud cybersecurity between 2010 and 2026. It highlights the evolution of cloud security from isolated perimeter defenses to a systemic challenge embedded within dynamic, multi-cloud, and containerized systems of systems. Key findings include:

1. **Exponential growth in publications**: Research output expanded from three papers in 2010 to 358 in 2025 (a compound annual growth rate exceeding 30%), driven by the integration of artificial intelligence and the adoption of cloud native architectures.

2. **Geographic volume versus impact**: India and China account for over 64% of total publications, whereas Western institutions (USA, Canada, UK, and Australia) maintain higher citation rates and greater centrality within the research collaboration network.
3. **Citation distribution**: The dataset demonstrates strong cumulative impact (H-index of 76; 29,322 citations) but also reveals 21.04% of papers remaining uncited (median = 4.0 citations).
4. **Thematic Evolution**: Research has progressed through three distinct phases: the foundational phase focusing on service models such as IaaS and virtualization (2010–2015). The phase centered on cryptography-based access and data privacy (2016–2020). Finally, the phase involving AI-driven threat detecting and preventing, the zero trust model, and cloud native methodologies (2021–2026).

6.2. Comparative Summary of Related Work

1. **Publication Growth:** Points of convergence: The exponential rise noted in this study aligns with broader trends in research literature documenting sustained growth in cloud security research (Cai et al., 2015; Dayyabu et al., 2020; Garg et al., 2019; Thiam et al., 2019). Divergence: While early foundational studies recorded moderate annual growth rates of approximately 15% (Thiam et al., 2019), recent specialized analyses indicate accelerated growth exceeding 30–36% annually affected by the adoption of deep learning technologies after 2016 (Alzoubi et al., 2024), the rise in artificial intelligence research after 2018 (Chuang & Chuang, 2026), and research on access control after 2020 (Reddy et al., 2026).
2. **Geographic Output and Impact:** Dominance in volume: All studies confirm that China and India lead in the volume of global publications regarding cloud security (Dayyabu et al., 2020; Garg et al., 2019; Thiam et al., 2019), particularly in the fields of machine learning (India) and deep learning (China) (Alzoubi et al., 2024; Reddy et al., 2026).

3. **Evolution of the Concept of Complexity:** Phase One (1) (Foundational): Early research focused on the isolation of static virtual machines within service models and the risks associated with hypervisors (Cai et al., 2015; Dayyabu et al., 2020). Phase Two (2) (Expansion): The focus shifted toward searchable encryption, Attribute-Based Access Control (ABAC), and organizational uncertainty regarding vendor maturity (Garg et al., 2019; Thiam et al., 2019; Zied Milian et al., 2017). Phase Three (3) (Systemic Complexity): Recently, research frames complexity around microservices, observability through federated learning, and post-quantum cryptography (Alzoubi et al., 2024; Judijanto & Vandika, 2026; Reddy et al., 2026).
4. **International Collaboration**: The international co-authorship rate in this chapter (26.84%) reflects a notable increase compared to previous rates of 6.6% (Cai et al., 2015). This aligns with recent estimates indicating a co-authorship range of 20% to 25%, centering on collaborative involving the United States and China, as well as the Middle East and Asia (Abdulle et al., 2026; Reddy et al., 2026).

6.3. Contribution of the Chapter

This chapter enriches the body of knowledge regarding bibliometric studies of cloud security in the following ways:

Conceptualizing Cybersecurity Complexity: Unlike previous bibliometric studies that treated cloud security as a monolithic topic or focused on specific technical sub-domains, our work establishes the concept of "cybersecurity complexity" as an explicit theoretical framework. Here, we clarify how various factors including structural interdependencies in multi-cloud and evolved architecture and technologies and AI automation, converge to increase operational vulnerabilities.

We also provide the research evolution and complexity assessment of cloud computing security architectures and technologies, enabling clear direction of research field.

Analytical monitoring through 2026: We present an up-to-date assessment that keeps pace with the accelerated pace of post-pandemic research, tracking the rise of federated learning technologies and other cybersecurity practices.

6.4. Emerging Topics and Future Directions

Addressing the fourth research question RQ4, keyword evolution analysis identifies several emerging research areas that will shape the future of cloud computing security research. First, the term federated learning has emerged as a rapidly growing keyword (30 times during the period 2021–2026, after being very rare in previous periods). This reflects the increasing interest in privacy preserving machine learning models that enable collaborative model training without sharing raw data (Rahdari et al., 2025). This is crucial in cloud computing environments where data protection regulations such as the European GDPR regulation, enforce strict limitations on data processing and sharing. Future research is likely to focus on improving the efficiency of federated learning frameworks in multi cloud and hybrid computing environments.

Second, the integration of blockchain technology with cloud computing security represents a significant emerging trend. The inherent characteristics of blockchain technology enable innovative approaches to address cloud computing security challenges such as access control and data integrity and sovereignty (Wei et al., 2020). Keyword frequency analysis reveals that blockchain and cloud computing (20 occurrences) and blockchain and cloud computing security (16 occurrences) are among the strongest links which indicates a growing research in this area. Third, threat detection using deep learning (as evidenced by the strong occurrence of cloud computing security and deep learning, 24 occurrences) is rapidly evolving, and future trends are likely to include

interpretable artificial intelligence for security purposes, machine learning countermeasures, and real-time threat intelligence systems.

Fourth, edge computing security is a promising field driven by IoT devices and the need for low latency security processing at the network edge. The frequent use of the term edge computing (28 times) alongside cloud computing indicates growing research interest in security challenges of cloud edge computing architectures. Fifth, the relatively low frequency of terms such as symmetric encryption (27 times) and searchable encryption (27 times) suggests that advanced encryption techniques remain crucial research area, to enabling secure computing on encrypted cloud data. These emerging trends point to a future of cloud computing security characterized mainly by intelligence models, decentralization learning and privacy preserving cryptography.

6.5. Implications and Limitations

The findings of this study offer several important implications for researchers, practitioners, and policymakers. For researchers, the identification of emerging topics such as federated learning, blockchain-based security and edge computing security, opens directions for future research. The average rate of international collaboration suggests that researchers should actively pursue cross border partnerships to integrate diverse perspectives and regulatory frameworks into their work. For practitioners, the focus on impactful research in specific IEEE journals and Elsevier provides guidance on how to access the most influential studies. For policymakers, the geographic focus of the research output highlights the need to invest in cybersecurity research capabilities in underrepresented regions, particularly in Africa, Latin America, and small European countries to ensure balanced and resilient global cybersecurity knowledge base.

This study is subject to several limitations that should be acknowledged. Relying on a single database (Scopus) may lead to biased coverage. Furthermore, keyword-based search queries may not include all relevant publications, particularly those implicitly addressing cloud

computing security. Future research could complement this analysis with data from multiple databases, utilize more author identification algorithms such as Open Reseacher and Contributer ID (ORCID) based matching, and conduct citation context analysis to better understand the practical applications of published research. Despite these limitations, this study provides a solid foundation for understanding the growing cybersecurity complexities of cloud computing.

7. Conclusion

This bibliometric analysis provides a comprehensive, data-driven map of the cybersecurity complexity research in cloud computing, based on 1,583 publications extracted from Scopus database, covering the period from 2010 to 2026. The analysis is structured around four research questions that collectively address research maturity, active contributors, the evolution, and research directions in the field.

The key findings are summarized as follows: (1) first, the field is experiencing rapid growth, with annual output increasing from 3 research papers in 2010 to 358 papers in 2025, reflecting a CAGR exceeding 30%, and emphasizing the increasing importance of cloud computing security research. (2) Second, India and China mainly dominate the research domain, together accounting for more than 64% of global output, with IEEE being the leading publisher. (3) Third, this field demonstrates a solid academic impact, with an h-index of 76 and a total of 29,322 citations, supported by key research papers that each received over 700 citations.

Fourth, thematic development reveals a clear progression from foundational cloud computing security (2010–2015), through expansion to include threat detection, privacy and risk management (2016–2020), to the current AI-driven standard including machine learning, deep learning, blockchain technology, and federated learning (2021–2026). Fifth, international collaboration remains moderate at 26.84%, with the strongest relations between China and the United States, and between Saudi Arabia and India.

Identifying federated learning, blockchain-based security, edge computing security, symmetric encryption, and machine learning as the most promising emerging research directions provides a roadmap for future academic research. As cloud computing continues to evolve and integrate with emerging technologies, the challenges of cybersecurity will become increasingly complex requiring ongoing research collaboration efforts.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, ChatGPT (OpenAI), Gemini, Consensus, and Manus were utilized for dataset analysis, language editing, and the summarization of papers and references. The author retains full responsibility for the content of the chapter.

Conflict of Interest: The author declares that there is no conflict of interest.

Funding: The author declares that this chapter received no financial support from any institution, project, or funding body.

Third-Party Materials and Permissions: No third-party figures, tables, images, or other materials requiring permission were used in this chapter. All figures and tables were prepared for this chapter and were not reproduced or adapted from third-party sources. The author confirms that no third-party materials requiring permission have been used in the chapter.

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Chapter 5:

The Impact of Artificial Intelligence on Organizational Change Processes: A New Change Management Paradigm?

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Abstract

Artificial intelligence (AI) is no longer merely used as a new technological tool in organizations; it is becoming one of the constitutive elements of decision-making, coordination, control, knowledge production, work design, and employee experience. This development raises the question of whether AI, beyond being an object of organizational change, is transforming how change emerges, by whom it is directed, and over what time horizon it is managed. The aim of this chapter is to critically evaluate the explanatory power of established change management approaches in the age of AI and to develop an integrated conceptual framework for explaining AI-mediated organizational change. Lewin's planned change approach, Kotter's model, organizational development, continuous change, organizational learning, dynamic capabilities, socio-technical systems, and technology acceptance approaches are compared in the context of AI's learnability, partial autonomy, opacity, and scalability. The conceptual synthesis indicates that the mechanisms of leadership, participation, communication, trust, and institutionalization emphasized by established approaches remain valid; however, assumptions of linear processes, a clearly defined end state, exclusively human agency, and one-off implementation are inadequate. The "double-loop AI change governance" model proposed in this chapter integrates the redesign of organizational task and decision architectures with monitoring the AI system throughout its life cycle in terms of performance, errors, fairness, and employee impacts. In conclusion, it is argued that it is premature to declare that AI constitutes an entirely new paradigm; nevertheless, it necessitates a substantial paradigm extension that reconceptualizes change management as a continuous, distributed, data-informed, and socio-technical governance capability.

Keywords: artificial intelligence, organizational change, change management, algorithmic management, human–AI collaboration, digital transformation, socio-technical systems

1. Introduction

Organizations' turn toward artificial intelligence is creating a transformation dynamic that differs from traditional information technology applications. Earlier digital systems, such as enterprise resource planning or process automation, also altered organizational structures and routines; however, contemporary AI systems enter directly into cognitive work through classification, prediction, recommendation, and content generation, participate in decision processes under certain conditions, and can be updated with new data during use. Generative AI's capacity to produce text, code, images, and analyses has transformed technology from a tool that merely executes predefined instructions into an active component of knowledge production. The impact of AI in organizations is therefore more extensive than the expression "transition to a new technology" can convey.

The fundamental distinction is between change carried out with AI and a change in the nature of change because of AI. In the first case, the organization selects and implements a particular technology and manages employees' adaptation to it. In the second case, AI participates in defining change-related problems, generating alternatives, monitoring employee behavior, and adapting interventions. Technology thereby becomes not only an object of change but also an element that shapes the change process. Redistributing decision rights between humans and algorithms does not eliminate the role of managers, but it changes where and how managerial judgment is exercised (Shrestha et al., 2019). Algorithmic management practices likewise transfer managerial functions such as performance measurement, task allocation, ranking, and rewarding to data-driven systems, thereby transforming both the manifestation of control and the way employees experience it (Kellogg et al., 2020).

The contemporary organizational effects of AI are not unidirectional. Brynjolfsson et al.'s (2025) field study in customer service shows that generative AI support can increase productivity and that the gains are concentrated particularly among less experienced employees. This finding suggests that AI can diffuse expert knowledge. At the same

time, the standardization of knowledge may render the distinctive contributions of experienced employees less visible, while excessive dependence on system recommendations may lead to skill erosion in the long term. Similarly, field evidence showing that individuals working with AI can approach team-level performance in certain tasks indicates that the technology can stretch expertise boundaries, but does not demonstrate that the social and emotional dimensions of collaboration have been entirely substituted (Dell'Acqua et al., 2026). Productivity gains alone are therefore not a sufficient criterion for explaining the success of organizational change.

This study adopts a conceptual review approach, conducted as a narrative (non-systematic) review of the literature through a socio-technical systems lens, to examine how artificial intelligence reshapes organizational change processes and the governance mechanisms through which these processes are managed. It draws on relevant literature on organizational change, change management, artificial intelligence, human–AI collaboration, and socio-technical systems. Rather than reporting an original empirical investigation or a systematic literature review, the chapter critically synthesizes these bodies of literature to compare established change management perspectives, identify their explanatory boundaries in the context of AI, and develop an integrated conceptual framework. The analysis is organized around the implications of AI for the temporality and agency of change, organizational decision-making, work design, governance, and the human experience of change. This conceptual synthesis provides the basis for the proposed Double-Loop AI Change Governance Model.

2. Conceptual and Theoretical Foundations

2.1. Artificial Intelligence, Generative Artificial Intelligence, and Algorithmic Management

Artificial intelligence can be defined as the set of computational systems that collect data from their environment and process these data

for purposes such as classification, prediction, recommendation, optimization, or content generation. This definition treats AI not as a holistic replica of human intelligence but as technical arrangements that perform specific cognitive functions to varying degrees. In an organizational context, defining AI solely in terms of its technical capacity is insufficient; the tasks undertaken by the system, how it affects decisions, and how it relates to the judgment of human actors must also be considered. Organizational AI should therefore be conceptualized not as an independent agent replacing human decision makers, but as a socio-technical arrangement in which managerial tasks and decision processes are redistributed between humans and algorithms (Benbya et al., 2020; Hillebrand et al., 2025).

Generative AI encompasses models that produce new text, code, images, audio, or similar content on the basis of patterns in existing data. In relation to generative AI, the capacity to "generate new content" must be distinguished from the capacity to "produce accurate and reliable information." A system's ability to generate fluent text, code, or recommendations does not mean that the content it produces has been verified. This distinction demonstrates that human oversight in organizations is not merely a technical safeguard but a design principle that protects decision quality and organizational accountability (Dwivedi et al., 2023; Jarrahi, 2018).

Algorithmic management refers to the use of data and algorithms in managerial functions such as task allocation, performance evaluation, scheduling, compensation, and discipline. Management does not disappear in this arrangement; rather, it becomes embedded in code, metrics, data-collection arrangements, and exception rules. Kellogg et al.'s (2020) discussion of "algorithmic control" shows that algorithms' capacities to direct, evaluate, and discipline also reshape employee contestation and accommodation strategies. Algorithmic management should therefore be understood not merely as an instrument of technical efficiency, but as an arrangement of power, visibility, and accountability.

2.2. Organizational Change, Change Management, and Digital Transformation

Organizational change is the differentiation that emerges over a given period in an organization's structure, processes, membership relations, goals, routines, or distribution of power. Change does not occur only in the form of projects planned by top management; it may also emerge through responses to environmental pressures, employees' everyday adaptations, organizational learning, and the accumulation of small adjustments. Organizational change is therefore a multilevel process that may be both planned and emergent, and both episodic and continuous (Huber ve Bartunek, 2016; Weick & Quinn, 1999).

Change management is not identical to change itself. Change refers to differentiation in the state of the organization, whereas change management refers to the managerial and participatory interventions used to direct, make sense of, implement, and institutionalize that differentiation. This distinction makes it possible to include in the analysis changes that are not directly planned by managers but arise through employee practices, technology updates, or environmental conditions (Burnes, 2004).

Digital transformation refers to comprehensive change through which digital technologies reshape an organization's value-creation logic, processes, and stakeholder relationships (Verhoef et al., 2021; Vial, 2019). Although AI transformation is a subset of digital transformation, it should be analytically distinguished because of three characteristics. First, AI generates outputs and influences decisions; it does not merely transmit information. Second, its performance depends on data quality and the context of use. Third, model behavior can change through updates, new inputs, and user interactions. These characteristics render the statement "implementation is complete" problematic. Even when an AI system has technically been deployed, organizational roles, oversight thresholds, and norms of use continue to evolve.

2.3. Human–AI Collaboration and Socio-Technical Formation

Human–AI collaboration refers to the complementary participation of a human and a computational system in a shared task or decision process. This relationship is not a simple division of labor; it is a reciprocal arrangement in which actors evaluate one another's outputs, are affected by one another's errors, and alter their usage strategies over time. The human–AI symbiosis emphasized by Jarrahi (2018) is based on the potential to combine human intuition and contextual judgment with the machine's pattern-recognition capacity. Complementarity, however, does not emerge automatically. Unless task boundaries, forms of explanation, channels for contestation, and responsibility for the final decision are designed, the hybrid system may amplify errors rather than combine the strengths of both parties.

The socio-technical systems approach is of central importance for understanding this issue. Since the work of Trist and Bamforth (1951), the core argument has been that technical and social subsystems should be jointly optimized. The effects of AI are not reducible to model accuracy; they emerge together with performance indicators, incentive systems, managerial behavior, employees' professional norms, and organizational culture. Orlikowski's (1992) approach to the structuration of technology likewise demonstrates that technology both shapes organizational action and is reshaped within practices of use. From this perspective, AI is not an independent variable that "acts upon" the organization from the outside, but a socio-technical component that acquires meaning and power within organizational practices.

3. A Critique of Established Change Management Approaches in the Age of AI

3.1. Lewin: Equilibrium, Process, and Participation

Lewin's (1947) approach to change is commonly presented as a linear model consisting of unfreezing, changing, and refreezing. This reading assumes that the organization is moved from an existing equilibrium to a new equilibrium. From the perspective of learning and frequently updated AI systems, the idea of "refreezing" initially appears inadequate because model performance, data distributions, and usage practices continue to change. Lewin's approach, however, should be considered not merely as a three-stage linear prescription but together with group dynamics and action research. Burnes (2004) demonstrates that, when read in conjunction with Lewin's group dynamics, field theory, and action research, the approach offers a participatory and iterative understanding of change.

What should be retained from Lewin in the age of AI is not the idea of "freezing the end state," but the logic of making the existing force field visible and enabling collective learning. When an algorithmic performance system is implemented, technical accuracy should be examined alongside employees' perceptions of fairness, how managers invoke the system, and the channels through which objections are addressed. Refreezing can be reinterpreted as a temporary governance settlement rather than permanent stability: which decisions may be automated, at which thresholds human review is required, and which data may not be used are tied to institutional rules that are periodically reconsidered.

3.2. Kotter and ADKAR: The Tension Between Managerial Mobilization and Linear Implementation

Kotter's eight-stage model offers practical mechanisms such as creating a sense of urgency, building a guiding coalition, developing a vision, communicating, removing obstacles, generating short-term wins, and embedding change in culture (Kotter, 1995). Top-management support, a shared vision, and early wins remain important in AI transformations. Particularly in projects characterized by high uncertainty, visible pilot results can translate abstract AI discourse into concrete organizational benefit. The problem arises when the model is read as a program initiated by management and progressing through sequential stages. Employees may begin using generative AI spontaneously before a formal strategy exists in many organizations. A model update by the technology provider may alter capabilities and risks even during the project's "implementation" stage. Under these conditions, top-down communication of a single vision is insufficient; a two-way process is required in which feedback from usage practices can modify strategy.

Jeffrey Hiatt proposed the ADKAR model to minimize resistance that may arise in organizational change and to enable change to proceed with an appropriate strategy. The model consists of five main components: Awareness, Desire, Knowledge, Ability, and Reinforcement. Awareness and Desire concern moving the individual out of the current state by recognizing that change is needed even though it has not yet begun. Knowledge and Ability relate to the change process itself, whereas Reinforcement focuses on the future after the change (Hiatt, 2006).

ADKAR's dimensions of awareness, desire, knowledge, ability, and reinforcement are useful for monitoring individual adaptation. Nevertheless, explaining adaptation to AI solely through individual motivation and skill may obscure system errors, organizational injustice, and the intensity of surveillance. An employee's objection to algorithmic evaluation is not always "resistance to change"; it may sometimes be a

valid governance signal concerning data quality, a breach of professional ethics, or inexplicable decisions. In such a case, the target of intervention should not be to change the employee's attitude, but to correct the system and the decision process.

3.3. Organizational Development, Continuous Change, and Sensemaking

The organizational development approach provides a strong foundation for AI transformation in terms of participation, feedback, group processes, and humanistic values. The diagnosis–intervention–evaluation cycle of action research is compatible with piloting AI applications and evaluating their outcomes together with employees. However, when conventional organizational development practices leave technology design to specialists and address social adaptation only afterward, socio-technical integrity is lost. AI teams, human resources, legal, risk, operations, and employee representatives should participate in the same design cycle.

Weick and Quinn's (1999) distinction between episodic and continuous change is particularly useful for explaining the temporality of AI. Episodic change refers to interventions with a defined beginning and end, whereas continuous change describes the cumulative transformation of the organization through everyday adaptations. AI transformation embodies both logics. Model selection, infrastructure investment, and workflow redesign can be conducted as episodic programs, whereas users' prompting practices, exception management, and levels of trust in the system change continuously. AI change management should therefore combine project management with a sensemaking capacity that monitors the continual re-formation of practices.

3.4. Organizational Learning, Dynamic Capabilities, and Technology Acceptance

The organizational learning perspective makes visible AI's bidirectional effects on knowledge production and organizational memory. AI can disseminate the knowledge of experienced employees to a broader group; yet when it obscures the source and context of that knowledge, it may create superficial standardization. Argyris and Schön's (1978) distinction between single-loop and double-loop learning is important here. Single-loop learning involves correcting errors while preserving existing goals. Double-loop learning questions the goals, assumptions, and decision rules themselves. Improving the accuracy of an AI system is single-loop learning; questioning why a particular decision has been automated and whether the performance criterion is fair is double-loop learning.

The dynamic capabilities approach focuses on an organization's capacity to sense opportunities, seize them, and reconfigure its resource base (Teece, 2007). In the AI context, sensing requires distinguishing a technological possibility from a business problem; seizing requires combining investments in data and capabilities with appropriate governance; and reconfiguring requires transforming tasks, decision rights, and competencies. Nevertheless, when the dynamic capabilities approach is not complemented by employee experience and power inequality, it risks reducing change to the strategic capacity of top management alone.

The Technology Acceptance Model and UTAUT explain the role of perceived usefulness, ease of use, social influence, and facilitating conditions in adoption (Davis, 1989; Venkatesh et al., 2003). These variables are important in AI use, but remain incomplete unless trust, explainability, professional identity, and fairness concerns are incorporated. An employee may find a system useful and easy to use yet refuse to use it because of the risk of harm to customers or ambiguity

regarding accountability. Acceptance is therefore not a behavioral outcome independent of ethics and organizational legitimacy.

4. The Impact of Artificial Intelligence on the Nature of Organizational Change

4.1. The speed and continuity of change

AI can increase the speed of organizational change through different mechanisms. First, by reducing the time spent on knowledge-intensive activities such as analysis, content generation, and problem solving, it enables change-related activities to be carried out more rapidly. Second, feedback from user interactions and operational data makes it possible to adjust processes at frequent intervals (Dell'Acqua et al., 2026). Speed, however, is not synonymous with change capacity. An organization may deploy a technical system rapidly, while employees' sensemaking regarding new responsibilities, the assessment of legal risks, and the development of trust relationships may take longer. The asymmetry between technical speed and social adaptation is one of the fundamental tensions of AI transformation.

Continuity does not arise solely from the model's learnability. Updates by AI providers, shifts in data patterns, users' development of new use cases, and changing regulatory expectations continuously redraw the boundaries of implementation (Te'eni et al., 2026). The aim of change management should therefore be to produce safe adaptability rather than to reach a fixed "future state." Continuous change should not mean continuous intervention; otherwise, employees may experience change fatigue. Effective governance clearly distinguishes which elements are experimental and changeable from which principles are stable. Model selection may change, for example, while the principles of non-discrimination, the right to contest decisions, and human responsibility remain stable.

4.2. Agency and Decision Architecture

In established narratives of change, top management initiates change, change leaders implement it, and employees adopt or resist it. In AI-mediated change, agency is more distributed. Data scientists shape the model's technical boundaries, vendors determine update schedules, legal units define limits of use, employees shape actual practices, and algorithms shape the options that become visible. An algorithm is not a morally or legally responsible agent; however, by ranking options, altering the distribution of attention, and rewarding particular behaviors, it produces agent-like effects on organizational action.

Shrestha et al. (2019) show that human and AI decisions can be arranged sequentially, in an integrated manner, or through delegation. What matters is to establish a more detailed decision architecture than simply asking, "Is the human in the loop?" At what stage does the human intervene? Does the person have sufficient information and time to evaluate the system's recommendation? Must the person justify a decision not to follow the recommendation? Who is responsible for the outcomes? If human approval is merely symbolic, the actual decision has been delegated to the algorithm despite the apparent presence of human oversight. Change management should therefore examine the actual distribution of decision rights rather than merely the labels attached to roles.

4.3. Work Design, Structure, and Coordination

AI's impact on work design cannot be reduced to an automation–augmentation dichotomy. Raisch and Krakowski's (2021) automation–augmentation paradox demonstrates that organizations simultaneously seek to delegate tasks to machines and enhance human capacity. Automating a task may make the remaining human work more meaningful, or it may reduce human work to exception and error management. Requiring people to deal continuously with difficult cases about which the system is uncertain can increase cognitive and emotional load. Conversely, reducing routine workload may create space for

judgment and customer relationships. The outcome depends less on the characteristics of the technology itself than on how work is repackaged.

When generative AI lowers the cost of accessing knowledge, functional boundaries may become more permeable. A marketing specialist may generate basic code, while a software developer may draft customer communications. Dell'Acqua et al.'s (2026) field study demonstrates that AI can contribute to the integration of expertise and enable individuals to obtain some of the benefits associated with teams. The organizational implication is not that teams become unnecessary, but that the reasons for forming teams change. While some coordination ties established for access to knowledge may weaken, new ties become necessary for ethical evaluation, critical judgment, and social support.

4.4. Power, Control, and Accountability

AI systems can increase organizational visibility: behaviors that were previously unrecorded can be measured, compared, and predicted. This visibility may improve resource allocation while simultaneously intensifying surveillance. Although algorithmic control may create the impression that rules are neutral, decisions about which data are collected, how objectives are defined, and who bears the cost of errors are managerial choices. As Pachidi et al. (2021) demonstrate, working with algorithmic systems creates new forms of negotiation between professional knowledge and data-driven recommendations. Rather than simply accepting or rejecting the system, employees interpret its outputs, sometimes work around it, and reposition their own expertise.

Attributing accountability to the technical system is a significant risk. The statement "the algorithm recommended it" can diffuse responsibility for a decision; yet it is the organization that selected the model, authorized data use, and defined oversight thresholds. AI governance should therefore include mechanisms for decision traceability, explanation, contestation, correction, and responsibility beyond performance accuracy. Particularly in hiring, promotion, compensation,

and disciplinary decisions that affect employees, explainability is not merely a technical feature but a condition of organizational justice.

4.5. The Transformation of Leadership and Change Agency

Leadership in the age of AI entails responsibilities broader than articulating a technology vision or encouraging employees to use a new tool. Leaders need to establish the connection between technical possibilities and organizational purpose, communicate uncertainties openly, and prevent performance pressures from exceeding ethical boundaries (Deb Biswas & Sengupta, 2026). A leadership discourse that acknowledges that AI can make errors does not necessarily create distrust of technology; on the contrary, it helps employees understand when the system can be trusted. Claims of certainty, by contrast, may damage organizational trust when the first visible error occurs.

Change agency in the age of AI cannot be conceived as the responsibility of a single manager or project team. Identifying risks arising from the development, implementation, and use of AI systems requires technical, organizational, legal, and societal dimensions to be assessed together and actors from different areas of expertise to participate in the process. Indeed, the use of teams representing different disciplines, experiences, and areas of expertise in AI risk management is important for making existing and emerging risks visible (National Institute of Standards and Technology [NIST], 2023). Similarly, organizational AI governance is regarded as a multidimensional governance problem requiring technical requirements to be considered together with organizational goals and values, stakeholder expectations, ethical principles, and legal obligations (Mäntymäki et al., 2022). Although this multi-actor structure necessitates strong coordination mechanisms, it can reduce the limitations associated with assessing AI's heterogeneous effects through a single domain of expertise. Nevertheless, distributing responsibility across numerous actors should not mean that accountability becomes ambiguous. Effective AI governance requires roles, responsibilities, decision authorities, and lines

of communication to be clearly defined. It is particularly important that top management retain responsibility for decisions concerning risks associated with the development and use of AI systems (NIST, 2023). Thus, while change agency in the age of AI becomes distributed and multidisciplinary, ultimate accountability must remain with clearly defined decision-making authorities.

4.6. Organizational Culture and Sensemaking

Organizational culture should be regarded as an important contextual factor affecting how AI systems are used within the organization beyond formal policies and procedures. Formally defining human oversight does not mean that employees will effectively question algorithmic recommendations. Particularly in organizational environments where employees avoid challenging managerial decisions, error reporting is not encouraged, or performance pressure displaces critical evaluation, the practical effectiveness of human oversight may weaken. This situation requires automation bias-the tendency for people to place excessive trust in the recommendations of automated systems and disregard their own judgment or conflicting information—to be evaluated not only as an individual cognitive tendency but also in conjunction with the organizational context in which AI is used.

Sensemaking processes become even more important when AI reshapes employees' tasks, responsibilities, and professional roles. When AI systems assume tasks or decision-making responsibilities that previously fell within employees' domains of expertise, they can affect employees' professional role identities and their assessments of the value of their expertise within the organization (Mirbabaie et al., 2022; Strich et al., 2021). Employees' concerns about whether AI will replace them, which aspects of their expertise will retain value, or which competencies will be expected of them in the future should therefore be addressed not merely as communication deficits, but as questions related to the professional identity and meaning dimensions of change. Given that AI's effect on employee identity may differ depending on whether the technology is used to complement or substitute human tasks (Selenko et al., 2022), it is

insufficient for change management to focus only on explaining the efficiency gains that AI may provide. Organizations should more clearly specify which tasks will be automated, in which areas human judgment and expertise will retain a central position, and the mechanisms that will support employees in adapting to changing roles, tasks, and skill requirements (Zhao et al., 2026).

The aim of cultural transformation is not to make everyone optimistic about AI. Critical curiosity is the appropriate cultural objective: employees should be able to experiment with the technology, question its outputs, report errors, and propose alternative work designs. In such a culture, skepticism is not equated with opposition to innovation. Organizational memory concerning the limitations of AI is developed; failed experiments are transformed into learning resources for subsequent applications rather than concealed.

5. The Human Dimension of Change

5.1. Trust, Justice, and Psychological Safety

Trust in AI does not mean accepting every system output as correct. Appropriate trust means using the system in proportion to its capabilities and limitations. Glikson and Woolley (2020) show that perceptions of tangibility, transparency, reliability, and technical capability affect trust in human–AI interaction. Low trust may lead to the non-use of a useful system, whereas excessive trust may result in automation bias. The aim of change management is not to maximize trust, but to calibrate it.

Distributive, procedural, and interactional justice should be considered together in AI applications. Who receives the benefits and bears the costs generated by the system? Is the decision process consistent and open to contestation? Are employees provided with respectful and comprehensible explanations? Even when a model's average accuracy is high, the implementation may lose legitimacy if the costs of errors are concentrated among particular groups. Psychological safety also requires employees to be able to voice AI errors, ethical concerns, and their own learning difficulties without fear of punishment. A culture that labels an

employee who reports an error as "anti-technology" renders system risks invisible.

5.2. Professional Identity, Autonomy, and Resistance

AI affects not only employees' tasks but also their understandings of "good work" and "expertise." The imitation within seconds by a model of judgment that an expert has developed over years may create a sense of status loss and devaluation. Conversely, reducing routine work through AI may strengthen the contextual and relational dimensions of expertise. The difference between these two outcomes is associated with employees' participation in the design process and their genuine autonomy over final decisions.

The concept of resistance should be reconsidered in this context. In the change literature, resistance has sometimes been presented as an irrational obstacle to be overcome. Employee objections, however, may reveal deficiencies in system data, potential customer harm, or invisible dimensions of work. In line with Ford et al. (2008), resistance is not independent of the discourse and actions of change agents. A productive approach in AI transformation is to investigate what risk information an objection carries rather than suppress it. Not every objection is necessarily valid; however, its validity should be tested empirically and ethically before the objective becomes persuading the employee.

5.3. Skill Transformation and Organizational Learning

AI literacy cannot be limited to the ability to use AI tools or interact effectively with these systems. AI literacy is a multidimensional domain of competence requiring individuals to understand the capabilities and limitations of AI systems, critically evaluate the outputs they generate, and consider the ethical and societal consequences arising from the use of these technologies (Long & Magerko, 2020). Reskilling and development

programs for employees that focus only on technical tool use may therefore be insufficient for developing the critical evaluation and ethical reasoning competencies required by AI literacy. Employees' ability to assess the reliability and limitations of AI outputs, recognize appropriate boundaries of use, and understand risks such as privacy, bias, and accountability should also be regarded as important components of AI literacy. Nevertheless, not every employee in an organization needs the same level of technical AI expertise. AI literacy requirements differ according to employees' organizational roles and the task and decision responsibilities they assume. Differentiating AI-related competencies by considering how senior managers, middle managers, and other employees interact with AI systems and the responsibilities they bear therefore offers a more appropriate approach to developing organizational AI literacy (Benlian & Pinski, 2025).

From an organizational learning perspective, the most critical risk is that short-term productivity gains may conceal long-term capability loss. Less experienced employees may perform rapidly with AI; however, if they use outputs without learning the reasoning underlying the solution, pathways to expertise may weaken. Training should therefore encompass not only producing more output with AI, but also sustaining fundamental judgment without AI and critically evaluating AI outputs. Job rotation, case review, peer review, and periods of "AI-free practice" in particular tasks may preserve skill resilience.

5.4. Job Security, Inequality, and Employee Voice

The integration of AI into organizational processes does not mean merely the adoption of a new technology for employees; it can also create uncertainty regarding the continuity of their jobs, the future content of their tasks, and the value of the professional resources they possess. In particular, the capacity of AI systems to perform cognitive tasks previously carried out by humans can increase employees' concerns that their jobs, or important components of their jobs, may be substituted by technology.

Recent research indicates that AI-related job insecurity is not limited to fear of complete job loss, but may also include a qualitative form of insecurity concerning the deterioration of valued features of work because of AI. Job-security concerns in AI transformation should therefore be treated not as temporary resistance that can simply be resolved through communication, but as genuine job and career uncertainty created for employees by technological transformation (Fu & Zhang, 2026).

Inequality in the organizational outcomes of AI need not be distributed evenly among employees. How the technology is developed, implemented, and used can affect which employees benefit from AI, who is subjected to more intensive evaluation and control, and under what conditions existing inequalities are reinforced. Recent literature examining the relationship between AI and workplace inequality shows that inequality does not arise only from biases encoded in algorithms; evaluative, compensation-related, and relational forms of inequality may emerge throughout the development, implementation, and use of AI systems within organizations. The organizational effects of AI should therefore be assessed not as outcomes predetermined by technology, but as processes shaped by the decisions and practices of organizational actors (Karunakaran et al., 2025).

Employee voice in AI transformation should not be conceived as a participation mechanism limited to soliciting employee opinions before implementation. Because AI and algorithmic management systems can change employees' tasks, the way their performance is evaluated, skill requirements, and working conditions, it is important that employees and their representatives be able to participate in decisions concerning the adoption and use of these systems. International examples concerning the use of AI in the workplace indicate that social dialogue can enable employee representatives to influence AI-related decisions in areas such as employment and skill effects, algorithmic management practices, and working conditions. Institutionalizing employee voice through ongoing social dialogue and representation mechanisms throughout the implementation and development of AI, rather than through one-off

consultation processes, can therefore be regarded as an important element of a more inclusive AI transformation (Doellgast et al., 2026).

6. A New Paradigm?

Whether AI requires a new paradigm in change management can be discussed, on the basis of the literature, through three possibilities: paradigm continuity, paradigm transformation, and paradigm extension.

According to the paradigm continuity view, AI is not wholly disconnected from technological changes that organizations have encountered before. Issues such as the joint adaptation of technology and employees, work redesign, preparing employees for change, and achieving alignment between social and technical systems were already central to change management. Makarius et al. (2020), for example, explain the integration of AI into organizations through established theoretical approaches such as socio-technical systems and organizational socialization. Their perspective demonstrates that successful AI integration requires technology and employees to be considered together. From this viewpoint, AI does not constitute a rupture that entirely invalidates established change management knowledge; rather, it introduces new conditions under which existing change mechanisms must operate.

The paradigm transformation view, by contrast, emphasizes that the learnability, generativity, and increasing autonomy of contemporary AI systems alter traditional assumptions concerning agency, expertise, authority, and decision-making in organizations. AI is no longer merely a passive tool used by employees; it can participate in knowledge production, judgment, coordination, and decision processes. Chalmers et al. (2026) show that different forms of AI reshape the location of expertise, judgment, coordination, and authority in organizations, generating new theoretical questions concerning the locus of agency and decision architectures. These characteristics challenge the assumption that change is a linear process designed solely by humans and directed toward a predetermined end state.

Nevertheless, the literature examined in this chapter supports an interpretation of paradigm extension rather than complete paradigm transformation. AI does not eliminate established change mechanisms such as leadership, trust, participation, sensemaking, and organizational learning; instead, it changes the socio-technical context in which these mechanisms operate. As Makarius et al. (2020) also demonstrate, the organizational value of AI depends on the successful integration of technology and employees.

To clarify the distinction between established change management assumptions and the proposed paradigm extension, Table 1 compares the two perspectives across five dimensions: temporality, agency, end state, success criteria, and governance. This comparison illustrates that the implications of AI are not limited to the introduction of a new technology. They also concern how change unfolds over time, which actors participate in shaping it, how organizational stability is understood, how success is evaluated, and how responsibility for technological and organizational outcomes is governed.

Table 1. Comparison of established change management assumptions and paradigm extension in the age of AI

Comparison Dimension	Established Understanding of Change	Paradigm Extension in the Age of AI
Temporality	Change is generally treated as an episodic process or project with defined beginning and end points.	Episodic change and continuous adaptation processes must be managed together.
Agency	Managers, leaders, and human change agents are positioned as the principal actors of change.	Agency extends to a broader socio-technical ecosystem including managers and employees as well as AI systems, technology providers, and regulatory actors.
End state	Change aims to reach a relatively stable state in which new practices have been institutionalized.	Rather than a definitive and permanent end state, temporary stability, continuous learning, and regular reassessment come to the fore.

Success criteria	Adoption, use, institutionalization of change, and organizational performance are the principal indicators of success.	In addition to performance, trust, fairness, organizational learning, accountability, and the reversibility of interventions when necessary are evaluated.
Governance	Emphasis is placed on planning and implementing change and on post-implementation control.	Monitoring, evaluation, risk management, and continuous assurance mechanisms are required throughout the AI system life cycle.

As shown in Table 1, the proposed paradigm extension involves changes in the assumptions underlying established change management approaches rather than the wholesale replacement of those approaches. First, the temporal dimension shifts from a predominantly episodic understanding of change toward the combined management of implementation and continuous adaptation. Second, agency is distributed across a wider socio-technical ecosystem in which human actors and AI systems jointly influence organizational processes, although their responsibilities and decision rights are not necessarily equivalent. Third, the notion of a stable end state is qualified by the need for ongoing learning and reassessment as AI systems, data, and work practices evolve.

The comparison also highlights a broader understanding of organizational success and governance. Adoption and performance remain relevant, but they are insufficient when considered independently of trust, fairness, accountability, employee effects, and the capacity to revise or reverse interventions when necessary. Similarly, governance cannot be confined to planning, implementation, and post-implementation control; it must also include the monitoring of system performance and organizational consequences throughout the AI life cycle.

These dimensions are interrelated. Continuous adaptation requires broader participation and feedback; distributed agency requires explicit decision rights and accountability; and the reassessment of outcomes requires governance arrangements capable of responding to new evidence. Table 1 therefore supports the argument that AI extends established

change management thinking by integrating continuous learning, socio-technical redesign, and life-cycle governance into the management of organizational change.

This extension does not require abandoning established theories, but rather explicitly recognizing their boundary conditions. When Lewin's action research, Weick and Quinn's continuous change, socio-technical joint optimization, and double-loop learning are considered together, a substantial portion of AI transformation can be explained. What is distinctive is the integration of these approaches with AI life-cycle governance and distributed decision architecture. Accordingly, the central contribution is not the claim that AI has rendered established change management theories obsolete, but that their application must be extended to account for the continuous, distributed, and socio-technical nature of AI-mediated organizational change.

7. Organizational Change Management in the Age of Artificial Intelligence: An Integrated Model

This chapter proposes the "double-loop AI change governance" model to explain AI-mediated change. The model consists of four layers: AI characteristics, organizational change mechanisms, mediating processes, and outcomes. Two simultaneous governance loops operate across these layers.

Figure 1 presents the Double-Loop AI Change Governance Model, which conceptualizes AI-enabled organizational change through four interdependent layers: AI characteristics, organizational change mechanisms, mediating processes, and outcomes. These layers are connected through two concurrent governance loops that guide organizational design, monitor the effects of AI implementation, and support continuous adjustment. The first layer, AI Characteristics, captures the capabilities, limitations, outputs, and potential risks of AI systems. The second layer, Organizational Change Mechanisms, concerns

how organizations define the problem to be addressed, classify tasks as automation, augmentation, or joint human–AI execution, establish decision rights and human-oversight thresholds, and redesign roles, competencies, and incentives. Together, these first two layers establish the technological and organizational conditions under which AI is introduced into work. The third layer, Mediating Processes**,** explains how AI-related characteristics and organizational change mechanisms are translated into organizational and employee outcomes. It comprises trust, perceived justice, organizational learning, and the quality of human–AI collaboration. These mechanisms are positioned between organizational change mechanisms and outcomes because they help explain how employees and organizations interpret, experience, and respond to AI-enabled change. The fourth layer, Outcomes**,** encompasses organizational and employee consequences, including change effectiveness and unintended effects. Feedback from these outcomes informs the reassessment of organizational objectives and change arrangements.

Two concurrent governance loops operate across all four layers. Governance Loop 1-Work and Organizational Design begins with defining the organizational problem and determining the appropriate role of AI. It proceeds through task classification, the allocation of decision rights, the establishment of human-oversight thresholds, and the redesign of roles, competencies, and incentives. Its central question is: *For what organizational purpose, in which tasks, and under whose responsibility should AI be used?*

Governance Loop 2-Lifecycle Assurance monitors the AI system and its organizational effects throughout the implementation lifecycle. Its scope includes model performance, errors, data drift, discriminatory outcomes, security, employee autonomy, and skill effects. Evidence generated through monitoring can trigger technical corrections and, where necessary, a reconsideration of the objectives, task allocation, or work-design choices established through Governance Loop 1. The two loops therefore operate concurrently: one guides organizational design and the allocation of responsibility, while the other evaluates system performance

and its broader consequences and feeds the resulting evidence back into design and governance decisions.

The relationships among the four layers and the operation of the two governance loops are shaped by contextual conditions, including organizational culture, leadership, AI maturity, employees' AI literacy, task uncertainty, and ethical governance. These conditions may influence the strength and direction of the relationships represented in the model.

Taken together, the model frames AI-enabled organizational change as an iterative socio-technical governance process rather than a one-time technology implementation. Figure 1 makes the relationship between the four layers, the mediating processes, the two governance loops, and contextual conditions explicit. In the figure, the four layers are arranged from left to right, with mediating processes positioned as the third layer between organizational change mechanisms and outcomes; Governance Loop 1 is shown above the layers, Governance Loop 2 below them, and the return arrow linking the two loops indicates that monitoring evidence and observed outcomes feed back into design decisions. The contextual conditions frame the entire model.

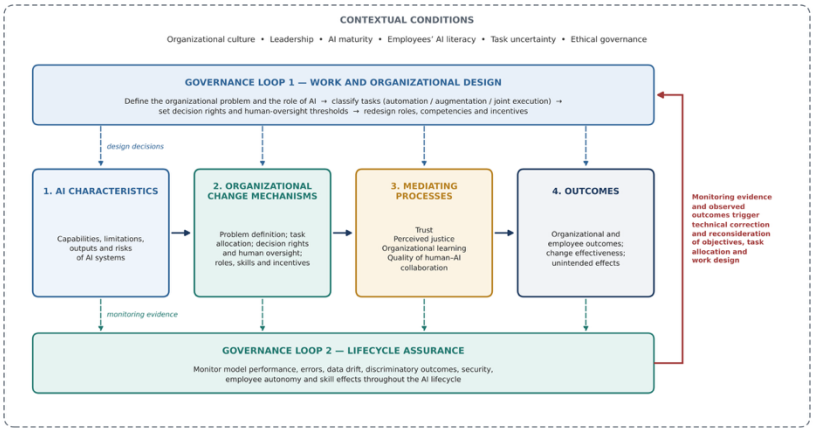


Figure 1. Double-Loop AI Change Governance Model

The model integrates four interdependent layers—AI characteristics, organizational change mechanisms, mediating processes, and outcomes—with two concurrent governance loops: work and

organizational design (Loop 1, shown above the layers) and lifecycle assurance (Loop 2, shown below the layers). Mediating processes comprise trust, perceived justice, organizational learning, and the quality of human–AI collaboration. Contextual conditions frame the model, while monitoring evidence and observed outcomes inform ongoing technical correction and organizational redesign.

Eight theoretical propositions can be derived from the model:

1. As the frequency with which the AI system is updated increases, the effectiveness of episodic change programs will become more dependent on continuous feedback and adaptive capacity.
2. Clearly defining decision rights between humans and AI will strengthen the positive effect of AI use on performance.
3. Meaningful employee participation in design and evaluation processes will increase appropriate trust through perceived procedural justice.
4. When algorithmic opacity is high, the absence of explanation and contestation mechanisms will increase resistance to change and informal avoidance behaviors.
5. The short-term productivity gains from AI-enabled standardization will be accompanied by long-term learning loss when critical judgment and practices of expertise development are not preserved.
6. Psychological safety will strengthen the relationship between employees' reporting of AI errors and risks and the organization's corrective capacity.
7. Double-loop governance that jointly monitors technical performance and employee impacts will produce more sustainable outcomes than single-loop governance that monitors model accuracy alone.
8. In organizations with high AI maturity, change management success will be explained more by the capacity for redesign and reversibility than by the adoption of individual projects.

These propositions make the model empirically testable. Longitudinal case studies, multilevel surveys, digital trace data, and field experiments can be used to examine the relationships between governance loops and employee and performance outcomes. The purpose of the model, however, is not to offer a single universal implementation prescription. Because the costs of error, professional autonomy, and regulatory conditions differ across healthcare, finance, manufacturing, and creative industries, the design principles should be adapted to context.

8. Discussion

The central contribution of this chapter is to explain AI-mediated organizational change as a socio-technical process in which technology shapes the course of change while remaining embedded in human decisions, institutional arrangements, and workplace practices. AI can influence which problems become visible, which options are considered, and how work is evaluated. Its organizational influence therefore extends beyond implementation, but this influence should not be confused with independent agency or moral responsibility: accountability remains with the people and institutions that design, procure, govern, and use these systems.

The Double-Loop AI Change Governance Model brings this argument together by connecting organizational and work design with life-cycle assurance. Its value lies in treating these activities as mutually corrective rather than as separate stages. Decisions about the purpose of AI, task allocation, and human authority shape the effects that must be monitored; evidence about performance, fairness, employee experience, and unintended consequences can, in turn, require the organization to revisit those original design choices. Trust, perceived justice, organizational learning, and the quality of human–AI collaboration help explain how this governance process translates into outcomes. The model thus integrates established change-management insights with an explicit mechanism for reassessing both the technology and the organizational arrangements around it.

This synthesis also changes how employee participation and resistance should be interpreted. Employee feedback is not only a means of securing acceptance: it can reveal mismatches between system outputs, professional knowledge, organizational values, and the realities of work. For this information to improve decisions, organizations need credible channels for questioning and correcting AI-supported decisions, clearly assigned decision rights, and sufficient authority to modify or suspend systems when warranted. These arrangements connect learning and participation to accountability rather than treating them as separate implementation activities.

The chapter's principal limitation is its conceptual character. The proposed relationships and eight propositions have not been empirically tested, and their relevance may vary across sectors, tasks, regulatory settings, and levels of AI maturity. Future research could examine the model longitudinally, comparing how the two governance loops affect decision quality, employee outcomes, organizational learning, and the ability to correct or reverse harmful interventions. Such research would help establish the conditions under which the proposed framework offers explanatory and practical value.

9. Conclusion

This chapter concludes that AI calls for an extension of change-management thinking, not the wholesale replacement of established theories. The distinctive challenge is to govern change when the technology being introduced can also shape decisions, work practices, and the information used to guide subsequent interventions. The contribution of the Double-Loop AI Change Governance Model is to make this recursive relationship explicit by linking organizational design choices to ongoing life-cycle assurance.

The broader implication is that responsible AI-enabled change depends on an organization's ability to learn from the consequences of its own design decisions. A change initiative should therefore be judged not only by whether a system is adopted or produces immediate efficiency

gains, but also by whether the organization can recognize adverse effects, preserve meaningful human judgment, assign accountability, and revise its approach in light of new evidence. This capacity for informed reassessment is the defining governance capability advanced in this chapter.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, generative artificial intelligence tools, specifically ChatGPT (OpenAI), Gemini, Consensus, and Manus, were used to assist with dataset analysis, language editing, the summarization of papers and references, and the development and refinement of a conceptual figure. The author reviewed all outputs and retains full responsibility for the content, interpretation, and final version of the chapter.

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Chapter 6:

Generative AI as a Co-Creator in Innovation Management

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Abstract

Generative artificial intelligence (GenAI) is reshaping innovation management by moving beyond its conventional role as a technological tool toward becoming an active participant in creative and decision-making processes. This chapter examines how GenAI can function as a co-creator across the innovation process and explores the complementary roles of human and artificial intelligence in generating meaningful innovation outcomes. Adopting a structured integrative literature review approach, the study synthesizes recent research on GenAI-enabled innovation through thematic analysis and conceptual synthesis. The findings indicate that GenAI contributes across multiple stages of innovation, including opportunity recognition, idea generation and evaluation, product and service development, business model innovation, commercialization, and organizational innovation. Its primary strengths lie in rapid content generation, knowledge synthesis, recombination, scenario development, and iterative refinement, whereas human contributors remain central to problem framing, contextual interpretation, strategic and ethical judgment, validation, and accountability. Building on these complementary capabilities, the chapter proposes the Human–GenAI Innovation Co-Creation Framework, which conceptualizes innovation as an iterative cycle of framing, generating, evaluating, refining, validating, and experimenting. The analysis further identifies hallucination, bias and idea homogenization, intellectual property concerns, human over-reliance, AI literacy, and organizational governance as important boundary conditions shaping the effectiveness of co-creation. Overall, the chapter argues that the transformative potential of GenAI in innovation management lies not in replacing human innovators but in designing organizational processes that deliberately combine human judgment and creativity with GenAI's generative and synthetic capabilities.

Keywords: generative artificial intelligence, innovation management, human–AI co-creation, human–AI collaboration, innovation process

1. Introduction

Innovation management has always been a discipline defined by the effort to organize uncertainty. Firms invest in structured processes for recognizing opportunities, generating ideas, evaluating alternatives, developing concepts, and bringing new products, services, and business models to market, precisely because the underlying activities are creative, ambiguous, and resistant to routine (Vocke & Bauer, 2020). Over the past two decades, digital technologies have progressively reshaped these processes: computer-aided design tools accelerated prototyping, digital platforms opened innovation to external contributors, and analytics systems supported evidence-based decision-making. Artificial intelligence extended this trajectory by adding predictive and classificatory capabilities—forecasting demand, screening patents, and flagging anomalies—without directly participating in the generative, judgment-intensive core of innovation work.

The emergence of generative artificial intelligence (GenAI) marks a qualitatively different moment in this trajectory. Unlike earlier digital tools, GenAI systems can produce novel textual, visual, and structural content on demand, at a pace and scale that was previously unattainable (Girotra et al., 2023). This capability arrives at a time when organizations already face intensifying pressure to innovate faster, under conditions of greater market volatility and information overload (Salminen et al., 2024). Firms are being asked to generate and evaluate a larger number of ideas, in shorter cycles, while maintaining—or improving—the quality, novelty, and feasibility of the outcomes. It is in this context that GenAI has moved from the periphery of innovation management research to its center.

Generative AI refers to a class of machine learning systems—most prominently large language models (LLMs) and increasingly multimodal foundation models—capable of producing coherent text, images, code, and structured design artifacts in response to natural-language prompts (Altun et al., 2026). These systems are trained on vast corpora and learn statistical regularities that allow them to recombine and synthesize existing knowledge into new configurations, rather than simply retrieving or

classifying pre-existing content. This is the crucial distinction between traditional AI and generative AI: whereas traditional AI applications in innovation management have historically supported prediction, optimization, and classification tasks, generative systems produce original outputs—drafts, alternatives, scenarios, and prototypes—that can be directly inserted into creative and decision-making workflows (Mariani & Dwivedi, 2024).

The practical accessibility of tools such as ChatGPT, and comparable systems for image, code, and design generation, has been a decisive factor in this shift. Because these interfaces require no specialized technical training, GenAI has diffused rapidly not only into research and development functions but into marketing, product management, and strategic planning more broadly (Kanbach et al., 2024). This combination of generative capability and ease of use is what distinguishes the current moment from earlier waves of AI adoption in innovation contexts.

A useful way to characterize this shift is to trace an evolving continuum of roles that AI systems occupy in innovation work. At one end, AI functions purely as a tool: a fixed-purpose instrument that executes a specific, narrowly defined operation—such as running a regression or automating a repetitive task—with no interpretive latitude. Moving along the continuum, AI can act as an assistant, handling well-specified sub-tasks (such as drafting a first version of a document) under close human direction. Further along, AI becomes a collaborator, participating iteratively in a shared task and adjusting its outputs in response to human feedback within a bounded exchange. Figure 1 summarizes this continuum.

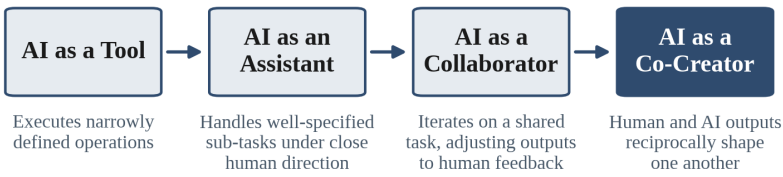


Figure 1. Evolution of AI's role in innovation

The concept explored throughout this chapter occupies the far end of this continuum: AI as a co-creator. In this role, GenAI does not merely execute instructions or await approval; its outputs actively shape the direction of the human's subsequent thinking, and the human's responses in turn reshape the AI's next contribution, in a mutually influencing cycle (Jiang & Wagner, 2026). Co-creation, in this sense, is defined not by the sophistication of the underlying model but by the structure of the interaction: it is a process in which neither party's contribution can be fully understood in isolation from the other's. This conceptualization is developed further in Section 5, where the distinction between human-in-the-loop supervision and genuine co-creation is examined in detail.

This chapter examines how Generative AI can function as a co-creator throughout the innovation management process, synthesizing the rapidly growing body of research on GenAI-enabled ideation, evaluation, development, and commercialization. It is guided by one overarching research question and three supporting questions:

Main RQ: How can Generative AI function as a co-creator throughout the innovation management process?

RQ1: What roles does Generative AI play across different stages of the innovation process?

RQ2: How does human–AI collaboration contribute to innovation outcomes?

RQ3: What challenges and boundary conditions influence Generative AI-enabled innovation co-creation?

The chapter's central argument is that Generative AI is evolving from a technological tool into an active co-creator that participates in the generation, development, evaluation, and commercialization of innovation, while human expertise, judgment, and governance remain essential for achieving meaningful innovation outcomes. The remainder of the chapter develops this argument through a review of conceptual foundations (Section 2), a description of the methodological approach (Section 3), a stage-by-stage analysis of GenAI's contributions across the

innovation process (Section 4), an examination of the co-creation dynamic itself (Section 5), a discussion of challenges and boundary conditions (Section 6), a proposed conceptual framework (Section 7), a discussion of theoretical and managerial implications (Section 8), and a concluding synthesis (Section 9).

2. Conceptual Foundations

2.1. Innovation Management

Innovation management is the deliberate organization of the activities through which firms identify opportunities and convert them into new or improved products, services, processes, business models, or organizational arrangements. Although accounts of the innovation process vary in granularity, most converge on a broadly sequential—if in practice iterative and recursive—set of stages: opportunity recognition, idea generation, idea evaluation, and development through to commercialization. To keep the analysis consistent, this chapter uses a single seven-part classification of the innovation process throughout (Section 4, Figure 2, and Table 2): opportunity recognition, idea generation, idea evaluation, product and service development, business model innovation, commercialization, and organizational innovation. Experimentation is not treated as a separate stage: prototyping and experimentation activities are discussed as part of product and service development (Section 4.4), and experimentation appears as the final step of the co-creation cycle described in Section 5.2. Business model innovation and organizational innovation, which extend the focus from products and services to how firms create and capture value and organize themselves, are included as stages of the same classification rather than as parallel categories. Innovation management, as a field, is concerned with designing the structures, capabilities, and decision rules that allow organizations to move through these stages efficiently while managing the inherent uncertainty of creative and market outcomes. It encompasses not only product innovation but also service innovation, business model innovation, and organizational or process innovation, each of which

follows a related but distinct logic. Because each of these activities depends on generating, combining, and evaluating information under uncertainty, innovation management has long been understood as a knowledge-intensive discipline—one to which GenAI, as a knowledge-synthesizing and content-generating technology, is particularly well suited to contribute.

2.2. Generative AI

For the purposes of this chapter, Generative AI is understood as a category of foundation models—including large language models and increasingly multimodal systems—capable of generating novel content across text, image, audio, and code modalities in response to natural-language input. Three capabilities are of particular relevance to innovation management. First, content generation: the ability to produce drafts of text, visual concepts, or code that can serve as raw material for further human refinement. Second, knowledge synthesis and recombination: the ability to draw on patterns learned from large and heterogeneous corpora and recombine them into configurations that may not previously have been explicitly articulated. Third, idea and scenario generation: the ability to produce multiple divergent alternatives—ideas, personas, future scenarios, or design variants—rapidly and at low marginal cost (Gindert & Müller, 2024; Girotra et al., 2023). This chapter deliberately avoids extended discussion of model architecture, training methodology, or the technical mechanics of transformer-based systems, since these details, while foundational to computer science, are largely orthogonal to the question of how GenAI functions within innovation management practice.

2.3. Human–AI Collaboration

A further conceptual foundation concerns the nature of human–AI interaction. The literature on human–AI collaboration distinguishes several related but distinct configurations. AI augmentation refers to the use of AI systems to extend human cognitive or perceptual capacity, without necessarily involving iterative exchange. AI-assisted decision-

making describes configurations in which AI provides recommendations or analyses that a human then incorporates into a decision, typically in a single pass. Human-in-the-loop approaches designate systems in which AI performs a task largely autonomously, subject to human supervision, correction, or approval at defined checkpoints. Co-creation, by contrast, is the configuration in which human and AI outputs continuously and reciprocally shape one another over multiple iterations, such that the resulting artifact cannot be attributed cleanly to either party alone (Kadenhe et al., 2025). This distinction between assistance and co-creation is conceptually important because it has direct implications for how organizations should design workflows, allocate responsibility, and evaluate innovation outcomes—implications that are developed at length in Section 5.

3. Methodology

3.1. Research Design

This chapter adopts a structured integrative literature review approach, combining thematic analysis with conceptual synthesis. The purpose of this approach is not to provide a statistically exhaustive account of the emerging GenAI literature, but to organize and interpret a rapidly developing and methodologically heterogeneous body of research in order to identify recurring patterns in human–GenAI collaboration across the innovation process. The chapter does not follow a full systematic review protocol (such as a pre-registered protocol with formal quality appraisal of each study); instead, the structured search and selection procedure described in Sections 3.2 and 3.3 is intended to make the identification of the relevant body of research transparent and traceable. Within this design, the thematic analysis component organizes that literature into recurring conceptual categories, and the conceptual synthesis component integrates these categories into the Human–GenAI Innovation Co-Creation Framework presented in Section 7. This combination of methods is appropriate for a topic such as this one, where the underlying phenomenon—GenAI-enabled innovation—is recent,

methodologically heterogeneous, and dispersed across several adjacent literatures (innovation management, human–computer interaction, creativity research, and information systems), such that a purely quantitative bibliometric approach would understate the conceptual richness of the field, while a purely narrative review would risk insufficient transparency.

3.2. Literature Search Strategy

The literature search was conducted in Scopus and Web of Science, given their broad coverage of peer-reviewed research in management, information systems, human–computer interaction, and related fields. The searches covered publications from 2020 to Jume of 2026. Two search strings were used as the final search strategy. The core string combined terms for generative AI with terms for innovation and co-creation:

("generative AI" OR "generative artificial intelligence" OR "large language model" OR "LLM") AND ("innovation management" OR "innovation process*" OR "innovation" OR "co-creation")

A second, complementary string focusing on human–AI interaction was run to capture studies on collaboration and co-creation that the core string might not retrieve in combined form.

("human-AI collaboration" OR "human-AI interaction" OR "AI co-creation")

Studies were included if they (a) were peer-reviewed journal articles, conference proceedings, or other emerging scholarly contributions (including preprints and working papers where no published version was available); (b) examined generative AI or large language models in relation to innovation activities, innovation management, or human–AI collaboration and co-creation; and (c) were published between 2020 and 2026, written in English. Studies were excluded if they did not meaningfully address these themes, and duplicate entries of same studies excluded.

3.3. Screening and Selection

The literature selection process was guided by thematic relevance, publication period, and the substantive contribution of each study to the understanding of Generative AI, innovation management, and human–AI collaboration. Particular attention was given to studies that examined the use of GenAI in innovation-related activities, including idea generation, evaluation, product and service development, decision support, organizational innovation, and business model innovation. The literature considered in this chapter covers recent contributions published primarily between 2020 and 2026 across fields such as innovation management, human–computer interaction, information systems, and related interdisciplinary domains.

Because this chapter follows a structured integrative literature review rather than a full systematic review protocol, the literature was organized to support the conceptual purpose of the chapter. Studies were therefore examined for their relevance to the central research questions and grouped according to recurring themes and analytical categories. The selection process emphasized peer-reviewed academic articles as well as relevant conference proceedings and emerging scholarly contributions where they provided substantive insights into GenAI-enabled innovation and human–AI collaboration. Publications that did not meaningfully address these themes were excluded from the analytical scope.

The resulting body of literature was not intended to constitute a statistically exhaustive sample of the entire GenAI research landscape. Instead, it served as the conceptual and empirical foundation for identifying recurring patterns, relationships, and tensions in the literature. Accordingly, the analysis focuses on the roles assumed by GenAI across different stages of innovation, the mechanisms through which human–AI collaboration may contribute to innovation outcomes, and the organizational and ethical conditions that may constrain such collaboration.

3.4. Thematic Analysis

The thematic analysis organizes the selected literature into eleven recurring codes: idea generation, idea evaluation, knowledge creation, product development, decision support, business model innovation, organizational innovation, creativity augmentation, human role, AI role, and risks and governance. These codes are not mutually exclusive, as individual studies may contribute to several themes simultaneously. Rather, they provide an analytical structure for synthesizing the literature and identifying recurring patterns across studies. [[The codes were developed through a combination of deductive and inductive steps. Codes that correspond to stages of the innovation process (idea generation, idea evaluation, product development, business model innovation, and organizational innovation) were defined in advance on the basis of the innovation management literature summarized in Section 2.1, whereas the remaining codes (knowledge creation, decision support, creativity augmentation, human role, AI role, and risks and governance) were derived from the reviewed studies as recurring themes emerged during reading. Each study was read in full and assigned to one or more codes according to the contributions reported in its findings; the coded studies were then grouped by theme and mapped onto the innovation stages discussed in Section 4 and onto the co-creation and boundary-condition themes discussed in Sections 5 and 6.]] In particular, the codes provide the organizing logic for Section 4, which maps the identified themes onto different stages of the innovation process, and Section 6, which brings together the risk- and governance-related themes to examine the boundary conditions of GenAI-enabled innovation and human–AI co-creation.

4. Generative AI Across the Innovation Process

This section examines GenAI's contribution along the single seven-part classification of the innovation process introduced in Section 2.1: opportunity recognition, idea generation, idea evaluation, product and service development, business model innovation, commercialization, and organizational innovation (Figure 2). The same classification structures

Table 2, which summarizes the stage-specific roles, representative activities, and illustrative outcomes at the end of this section. As noted in Section 2.1, these stages are treated as iterative and recursive rather than strictly linear.

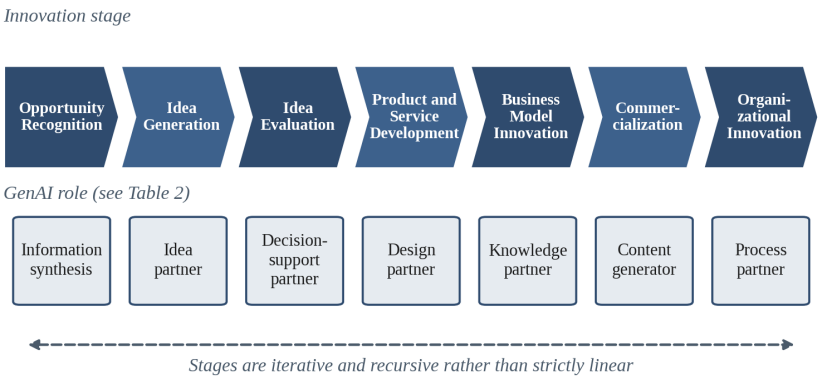


Figure 2. Generative AI across the innovation management process

4.1. Opportunity Recognition

The earliest stage of the innovation process involves identifying gaps, unmet needs, or emerging possibilities in the environment—monitoring market trends, customer needs, emerging technologies, competitor activity, and weak signals that may indicate a shift worth pursuing. GenAI's contribution here is primarily one of information synthesis: large language models can rapidly summarize and cross-reference large volumes of unstructured text—reports, reviews, forum discussions, and technical literature—surfacing patterns that would otherwise require extensive manual analysis. However, the framing of a problem as worth pursuing, and the judgment as to which weak signal is strategically significant, remains a distinctly human activity. This division of labor—AI information synthesis paired with human problem framing—recurs throughout the innovation process and is a first indication of the complementarity theme developed more fully in Section 5.

4.2. Idea Generation

Idea generation is the stage at which GenAI's contribution has been most extensively studied to date. Empirical work comparing GenAI-generated ideas with those produced by trained human participants has found that large language models can generate a substantially higher volume of ideas, more quickly and at lower cost, and that a meaningful share of the highest-quality ideas in pooled human–AI samples originate from the AI system rather than from human participants (Girotra et al., 2023). Related field-experimental work confirms that GenAI-augmented teams can produce higher-quality ideas in less time, while also reporting ancillary benefits such as improved knowledge exchange, greater engagement, and increased idea diversity (Gindert & Müller, 2024). At the same time, this literature is careful to separate idea quantity from idea quality: rapid generation of many alternatives does not by itself guarantee that any given idea is useful or original. Steppe et al. (2025) show that prompting a language model to generate ideas does not, on its own, augment creativity; rather, the creativity-enhancing effect emerges through iterative perspective-taking and refinement of the AI's initial output, which increases the comprehensiveness of the idea set and helps identify the ideas that are both novel and useful. In a related interview-based study, Quiel et al. (2026) similarly find that GenAI reshapes organizational ideation by expanding the sources from which ideas can be drawn, while the ultimate creative contribution continues to depend on how organizations structure the adoption and use of these tools. Taken together, this body of work suggests that GenAI expands the searchable space of possible ideas and lowers the cost of exploring it, but that the translation of this expanded space into innovation value depends on subsequent human evaluative and developmental work.

4.3. Idea Evaluation

Once a pool of candidate ideas has been generated, organizations must evaluate them—assessing strengths, weaknesses, risks, and market fit, often through structured techniques such as SWOT or comparative

and scenario analysis, and incorporating customer perspectives. GenAI can support this stage by rapidly producing structured comparative analyses, simulating customer reactions or stakeholder perspectives, and flagging risks that a purely qualitative review might overlook. Conceptual work on AI-augmented new product development similarly positions transformer-based language models as tools that widen the problem and solution space explored by human teams rather than as substitutes for them (Bouschery et al., 2023). Evidence on the quality of AI-supported evaluation remains limited and conditional, however. In a study comparing GPT-4 with human experts, Kranzle and Sharratt (2025) find that LLM evaluations reach only moderate alignment with expert judgments, and only when the model is guided by a base evaluation framework and a spectrum-based few-shot prompt; the authors recommend using such frameworks primarily for large-scale idea screening and caution that privacy considerations arise when third-party models are used to assess proprietary ideas. Taken together, these findings point to a consistent recommendation: AI-supported evaluation should be followed, not replaced, by human judgment, particularly where evaluation criteria involve strategic fit, ethical considerations, or tacit organizational knowledge that is not well represented in the AI's training data. This pattern—AI-supported evaluation followed by human judgment—mirrors the sequencing already observed in ideation and reinforces the complementary rather than substitutive character of GenAI's contribution to innovation decision-making.

4.4. Product and Service Development

Beyond idea generation and evaluation, GenAI is increasingly used to support the more concrete work of developing product and service concepts—drafting feature lists, generating user stories, producing design alternatives, mapping customer journeys, and supporting rapid, low-cost experimentation with prototypes (experimentation is treated here as part of product and service development rather than as a separate stage). In engineering design contexts specifically, a recent survey of the literature identifies five domains in which large language models are being applied:

ideation and conceptual design, requirements engineering and problem definition, knowledge retrieval and documentation, computer-aided design and engineering automation, and systems engineering and decision support (Altun et al., 2026). Reported benefits in this literature include accelerated concept generation, reduced documentation burden, and more intuitive access to legacy technical knowledge, generated or modified directly from natural-language prompts. In service contexts, GenAI has similarly been used to integrate stakeholder input more directly into the early stages of service concept development, addressing a long-standing cause of new-service failure—namely, launching services without an adequately deep understanding of stakeholder needs (Noack et al., 2025). In collaborative new-product development settings, GenAI-based tools have been shown to expand the collective cognitive boundaries of development teams and to improve knowledge integration during early-stage work, although their contribution to deeper analytical reasoning, negotiation, and solution integration appears comparatively more limited, and teams that rely on such tools risk a degree of reduced collaborative naturalness and over-reliance on AI-generated suggestions (Zhang et al., 2026).

4.5. Business Model Innovation

GenAI's generative and synthetic capabilities extend beyond individual products and services to the business model level, informing value propositions, revenue models, customer segmentation, and channel strategy—often in conjunction with established frameworks such as the Business Model Canvas. A scoping review drawing on more than five hundred data points—spanning academic publications, company reports, and public commentary—proposes six propositions describing GenAI's impact on business model innovation and illustrates these with industry examples from software engineering, healthcare, and financial services (Kanbach et al., 2024). A complementary multiple-case study across eight firms of varying size and industry finds that GenAI's contribution to business model innovation is uneven across the three classic dimensions of value creation, value proposition, and value capture: firms find it

comparatively easier to innovate on value creation, more difficult on value proposition, and hardest of all on value capture, with genuinely architectural business model innovation—changes that reconfigure both internal and external structures—remaining a substantial challenge even for firms actively experimenting with GenAI (Ramaul et al., 2024). A further contribution in this stream cautions that, alongside its evident opportunities, GenAI's use in business model innovation is bounded by real technological limitations, and that firms must couple adoption with attention to new employee skills and security considerations if they are to capture GenAI's potential benefits without incurring undue financial, reputational, or legal risk (Stolyarov et al., 2024).

4.6. Commercialization

At the commercialization stage, GenAI supports the generation of marketing concepts, advertising copy, branding material, and broader content for customer communication, alongside customer segmentation and the design of communication strategies. Kshetri et al. (2024) conclude that using GenAI to create marketing content can raise the efficiency and productivity of marketing activities, and that GenAI-generated insights and content can improve the sales lead generation process, although they also discuss barriers to its use in marketing. In line with this evidence, and as with idea generation, the productivity gains available at this stage are considerable: GenAI can produce multiple campaign variants, tailored messaging for different segments, and draft creative assets far more rapidly than manual processes allow. The trust-related concerns discussed in Section 6 are especially salient here, since commercialization content is customer-facing and therefore carries reputational risk if AI-generated outputs are inaccurate, biased, or perceived as inauthentic (see also Stolyarov et al., 2024, on the financial, reputational, and legal risks of GenAI adoption).

4.7. Organizational Innovation

Finally, GenAI contributes to innovation not only in market-facing outputs but in the internal processes and structures of the organization itself—supporting workflow redesign, knowledge management, process innovation, decision support, and organizational learning. A case study of an LLM-based chatbot developed to support process modeling within a multinational manufacturing organization illustrates this application directly: developed in response to pain points identified by professional process modelers, the tool was found to meaningfully assist in the creation of process flow diagrams, offering a concrete example of how GenAI can be embedded into organizational innovation practice beyond the domain of product or service development (Ziche & Apruzzese, 2024). More broadly, GenAI's capacity to synthesize and structure organizational knowledge positions it as a potential enabler of organizational learning, provided that firms develop the complementary capabilities discussed in Section 6.5.

Table 2 summarizes the stage-specific roles of GenAI across the seven stages examined in this section, together with representative activities and illustrative outcomes.

Table 2. Applications of generative AI across innovation stages

Innovation Stage	GenAI Role	Representative Activities	Illustrative Outcomes
Opportunity recognition	Information synthesis	Summarizing market, customer, and competitor signals	Faster, broader environmental scanning
Idea generation	Idea partner	Brainstorming, analogical thinking, scenario generation	Higher idea volume and variance in quality
Idea evaluation	Decision-support partner	SWOT/scenario analysis, simulated customer feedback	Structured, AI-supported human evaluation
Product and service development	Design partner	User stories, prototypes, design alternatives, rapid experimentation	Faster concept iteration, reduced documentation effort
Business model innovation	Knowledge partner	Value proposition and revenue model variants	Easier value-creation innovation; harder value-capture innovation

Commercialization	Content generator	Marketing copy, branding, segmentation	Faster, more tailored go-to-market content
Organizational innovation	Process partner	Workflow redesign, knowledge management, process modeling	Improved knowledge integration and process documentation

5. Human–GenAI Co-Creation

5.1 Complementarity Between Human and AI Capabilities

The analysis in Section 4 consistently points to a pattern of complementarity rather than substitution. Human capabilities central to innovation include domain expertise, strategic judgment, contextual understanding, creativity, ethical judgment, and accountability—capacities that are difficult to encode fully into a statistical model and that carry legal and organizational responsibility that cannot be delegated to a machine. GenAI capabilities, by contrast, center on knowledge synthesis, rapid generation of alternatives, pattern recombination, scenario generation, rapid iteration, and large-scale information processing. Ali (2025), synthesizing findings from a systematic review of over one hundred peer-reviewed studies through an Antecedent–Mediator–Moderator–Outcome framework, similarly concludes that successful human–AI integration depends on aligning human judgment with algorithmic capability, built on mutual trust, transparency, and interpretability, with cognitive complementarity emerging as a key mediating mechanism linking collaboration to innovation outcomes. This complementarity is not incidental; it is the structural feature that makes co-creation, rather than automation, the appropriate frame for understanding GenAI's role in innovation. Table 3 summarizes these complementary capabilities.

Table 3. Human and GenAI capabilities in innovation

Dimension	Human Capabilities	GenAI Capabilities
Knowledge	Domain expertise, tacit and contextual knowledge	Knowledge synthesis and recombination across large corpora
Idea work	Creativity, problem framing, originality judgment	Rapid generation of alternatives, scenario variation
Evaluation	Strategic judgment, ethical judgment, ecological validity checks	Structured comparative analysis, pattern-based risk flagging
Process	Accountability, stakeholder management, validation	Rapid iteration, low-cost refinement of drafts
Outcome ownership	Decision authority, responsibility for outcomes	No independent accountability; outputs require human ratification

5.2. The Co-Creation Cycle

Building on this complementarity, GenAI-enabled innovation can be represented as a recurring cycle: human problem framing initiates the process; GenAI idea generation produces an initial set of alternatives; human evaluation assesses and selects among them; GenAI refinement develops the selected direction further; human validation confirms strategic and contextual fit; and experimentation tests the resulting concept against real-world conditions, feeding results back into the next iteration. These six steps describe the pattern of interaction between human and GenAI contributors; they are distinct from the seven innovation stages discussed in Section 4, and the experimentation step corresponds to the experimentation activities embedded in product and service development (Section 4.4). It is important to emphasize that this cycle should be understood as iterative rather than linear—a recurring exchange of human ↔ GenAI ↔ human ↔ GenAI—rather than a single hand-off from machine to human or vice versa. Empirical models of this cycle bear this out: the two-stage model proposed by Jiang and Wagner (2026) similarly frames co-creation as an AI-seeded ideation stage, in which the AI establishes a foundation of readily generated ideas, followed by a human-enhanced ideation stage, in which humans engage in less patterned, more exploratory refinement that both improves the initial ideas and introduces content that would not otherwise have been included, extending traditional accounts of process gains and losses in collaborative

creativity. Pedota et al. (2025) offer a complementary formal account, conceptualizing GenAI as a superposition of latent possibilities from which optimal creative outcomes arise when human agents actively select the most contextually appropriate entity, converging asymptotically toward better outcomes through repeated iteration—a formalization that gives analytical grounding to the intuitive picture of the co-creation cycle described above.

5.3. Human-in-the-Loop versus Human–AI Co-Creation

The distinction introduced in Section 2.3 between human-in-the-loop supervision and genuine co-creation deserves further elaboration here, because it carries direct implications for innovation management practice. In a human-in-the-loop configuration, the AI system performs a task largely autonomously, and the human's role is to supervise, review, and approve or reject the output at a defined checkpoint; the direction of influence is therefore largely one-way, from AI to human. In a co-creation configuration, by contrast, human and AI outputs continuously and reciprocally shape one another, such that the resulting artifact reflects an ongoing exchange rather than a single machine-generated draft subjected to a single human check. This distinction matters for innovation management because it affects where organizations should invest in training, how they should structure review processes, and how they should think about accountability: a human-in-the-loop process places the weight of accountability on the final approval step, whereas a co-creation process distributes engagement—and therefore also the opportunity to catch errors or introduce originality—across the entire interaction. Kadenhe et al. (2025) develop a related point in their review of human–AI co-design, arguing that mixed-initiative and explainable-AI approaches are important precisely because they allow designers to engage in this kind of iterative, trust-based exchange rather than a single-pass approval workflow.

5.4. AI as a Cognitive Partner

Drawing these threads together, GenAI can be understood as occupying several overlapping cognitive-partner roles within the innovation process: an idea partner, generating and varying candidate concepts; a knowledge partner, synthesizing and retrieving relevant information; a design partner, producing and iterating on visual or structural artifacts; and a decision-support partner, structuring comparative or scenario-based analysis to inform human choices. It is important, in describing these roles, to avoid framing GenAI as possessing human-like cognition, intention, or understanding. The value of these partner roles lies not in any claim about the AI's inner cognitive states but in the functional complementarity they provide: GenAI reliably performs certain generative and synthetic functions well, and organizations benefit from designing workflows that pair these functions deliberately with the judgment, contextual understanding, and accountability that only human contributors can supply. Hirst et al. (2025) provide direct empirical support for the importance of this pairing, showing that training workers in prompt engineering, combined with more human-like AI interface design, produces substantial improvements in co-creativity outcomes—particularly when the two interventions are combined—underscoring that the quality of human–GenAI co-creation is not fixed by the technology alone but is actively shaped by how organizations invest in worker skills and interface design.

6. Challenges and Boundary Conditions

6.1. Hallucination and Reliability

A first and widely documented boundary condition is the tendency of generative models to produce plausible-sounding but factually incorrect content, commonly referred to as hallucination. In innovation contexts, this creates a verification burden: outputs that inform market sizing, technical feasibility, or competitive positioning must be checked against reliable sources before being acted upon, since the fluency of GenAI-

generated text can create an unwarranted impression of accuracy. This concern is a central reason why the literature reviewed in Section 4 consistently frames GenAI's evaluative and analytical contributions as inputs to human judgment rather than as final determinations.

6.2. Bias and Idea Homogenization

A second boundary condition concerns algorithmic bias and the risk of idea homogenization. Because generative models learn statistical patterns from existing data, their outputs can reproduce and amplify biases present in that data, and similar prompts—especially when used repeatedly across an organization or industry—can produce similar outputs, potentially narrowing rather than expanding the diversity of ideas under consideration. This concern is reinforced by experimental evidence from a visual ideation task, in which participants who used an AI image generator during ideation exhibited higher fixation on the AI's initial example and subsequently produced fewer ideas, with less variety and lower originality, than a non-AI baseline (Wadinambiarachchi et al., 2024). This finding is a useful corrective to an overly optimistic reading of the ideation literature reviewed in Section 4.2: GenAI's capacity to expand the space of possible ideas is real, but it is not automatic, and depends heavily on how users approach prompt construction and how they respond to the AI's suggestions.

6.3. Intellectual Property and Ownership

A third boundary condition concerns intellectual property and ownership. Because generative models are trained on large corpora that may include copyrighted material, questions arise regarding the provenance of AI-generated content and the extent to which such content can be protected, licensed, or claimed as proprietary by the organization that generated it. Mariani and Dwivedi (2024) identify GenAI-enabled innovations and intellectual property as one of ten priority research themes at the intersection of GenAI and innovation management, underscoring that firms adopting GenAI in product development or commercialization contexts need clear internal policies governing the

ownership and permissible use of AI-generated content, particularly where such content contributes directly to patentable or brand-defining outputs.

6.4. Human Over-Reliance

A fourth boundary condition concerns the risk of human over-reliance on GenAI outputs, sometimes described as automation bias. Where organizational members come to trust AI-generated suggestions uncritically, the risk is not only that specific errors go unchallenged, but that critical thinking skills atrophy over time (deskilling) and that human agency in decision-making processes is gradually diminished. Zhang et al. (2026) document a related pattern in collaborative new-product development, observing that heavy reliance on GenAI-generated suggestions during collaborative work can reduce the naturalness of team collaboration itself, suggesting that over-reliance is not only an individual-level risk but can also degrade collective processes.

6.5. Organizational Capabilities

A fifth and more structural boundary condition concerns the organizational capabilities required to realize GenAI's potential contribution to innovation. These include AI literacy among employees, overall digital maturity, adequate data infrastructure, a receptive organizational culture, engaged leadership, and governance capabilities sufficient to manage the risks described above. Corvello (2025), applying a Technology Appropriation lens grounded in Adaptive Structuration Theory, argues that the impact of GenAI on innovation management is not determined by the technology alone but emerges through the ways in which organizations customize, reinterpret, and negotiate power dynamics around its use—implying that two organizations adopting the same GenAI tools may realize very different innovation outcomes depending on their organizational context and appropriation practices. Piller et al. (2024) add a complementary trust-based perspective, proposing that the appropriate level of trust placed in GenAI outputs should vary with task-specific needs and with the distinction between general-purpose and domain-expert models: inaccuracies in GenAI output may be tolerable, or

even creatively productive, during early-stage ideation, but tasks requiring domain-specific expertise demand higher accuracy and correspondingly higher organizational scrutiny. Table 4 summarizes these challenges, their descriptions, and the corresponding governance mechanisms.

Table 4. Challenges, risks, and governance mechanisms

Challenge	Description	Governance Mechanism
Hallucination and reliability	Fluent but factually incorrect outputs	Mandatory human verification of AI-generated claims
Bias and idea homogenization	Reproduced bias; convergent outputs from similar prompts	Prompt diversification; deliberate diversity checks on idea sets
Intellectual property and ownership	Unclear provenance and ownership of AI-generated content	Internal IP policies for AI-assisted outputs
Human over-reliance	Automation bias, deskilling, reduced critical thinking	Defined human checkpoints; training in critical evaluation
Organizational capabilities	Gaps in AI literacy, infrastructure, and governance	Investment in training, data infrastructure, and leadership sponsorship

7. Conceptual Framework

Synthesizing the preceding sections, this chapter proposes a Human–GenAI Innovation Co-Creation Framework, organized into four layers surrounded by a set of contextual conditions. The framework is presented in Figure 3.

Layer 1 – Human Capabilities comprises the distinctly human contributions to the innovation process: domain expertise, creativity, judgment, and strategic thinking. These capabilities are what allow raw, AI-generated alternatives to be interpreted, evaluated, and connected to organizational strategy and market context.

Layer 2 – GenAI Capabilities comprises the generative and synthetic contributions of the technology: generation, synthesis, recombination, simulation, and refinement. These capabilities expand the pool of alternatives available for human consideration and accelerate the iterative development of selected concepts.

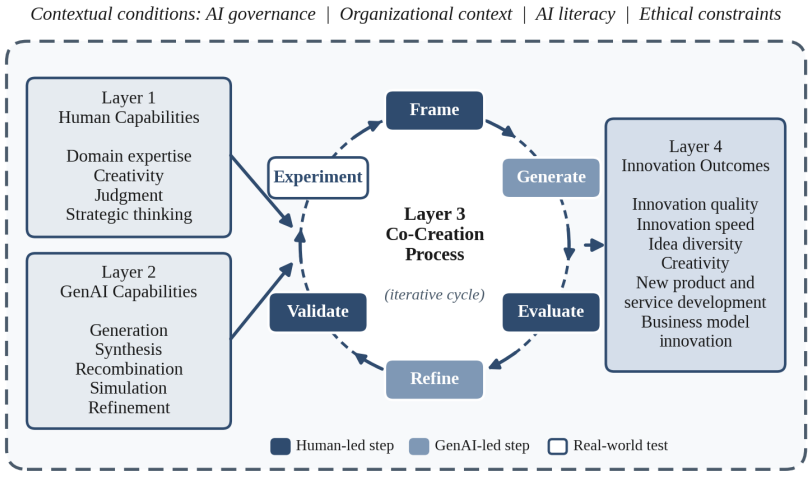


Figure 3. Human–GenAI innovation co-creation framework

Layer 3 – Co-Creation Process links these two capability layers through the recurring cycle described in Section 5.2: frame, generate, evaluate, refine, validate, and experiment. This layer is deliberately depicted as cyclical rather than linear, reflecting the finding, developed throughout Sections 4 and 5, that GenAI's contribution to innovation is most effective when embedded in iterative human–AI exchange rather than a single generative pass followed by a single human check.

Layer 4 – Innovation Outcomes comprises the downstream results that the co-creation process is intended to produce: innovation quality, innovation speed, idea diversity, creativity, new product and service development, and business model innovation. These outcomes correspond directly to the stage-specific contributions documented in Section 4.

Surrounding these four layers are the contextual factors identified in Section 6: AI governance, organizational context, AI literacy, and ethical constraints. These factors do not operate as a separate stage of the process but as conditions that shape how effectively the co-creation cycle in Layer 3 can translate the capabilities in Layers 1 and 2 into the outcomes in Layer 4. A firm with strong human capabilities and full access to capable GenAI tools, but weak AI governance or low AI literacy, would be expected—on

the logic of this framework—to realize a smaller share of the potential innovation outcomes than a comparable firm with stronger contextual conditions. This framework constitutes the principal conceptual contribution of the chapter and provides a structure against which future empirical research can be organized and tested.

8. Discussion and Implications

8.1. Theoretical Implications

This chapter's synthesis contributes to three adjacent literatures. First, it contributes to the human–AI co-creation literature by consolidating the distinction between human-in-the-loop supervision and genuine co-creation, and by integrating recent empirical models of co-creation (Jiang & Wagner, 2026; Pedota et al., 2025) into a stage-based account that connects directly to innovation management practice. Second, it contributes to the innovation management literature by explicitly reframing AI's role along a continuum from tool, to assistant, to collaborator, to co-creator—extending prior stage-based accounts of GenAI adoption in innovation (Mariani & Dwivedi, 2024) with a more granular account of the interactional dynamics involved. Third, it contributes to Generative AI research by consolidating evidence, drawn from ideation, evaluation, development, business model innovation, and commercialization contexts, that supports a complementarity-based rather than a substitution-based account of GenAI's organizational impact.

8.2. Managerial Implications

For practitioners, three implications follow directly from the analysis. First, organizations should deliberately design innovation processes around the complementary capabilities identified in Layer 1 and Layer 2 of the framework in Section 7, rather than either withholding GenAI adoption out of caution or delegating innovation decisions to GenAI outputs without adequate human evaluation. Second, human judgment should remain central to strategic and ethical decisions throughout the innovation process—particularly at the evaluation,

validation, and commercialization stages, where the reputational, legal, and strategic stakes of an error are highest. Third, AI literacy and governance capabilities should be built alongside GenAI adoption rather than treated as a subsequent concern: the boundary conditions reviewed in Section 6 indicate that firms which adopt GenAI tools without corresponding investment in employee training, data infrastructure, and governance mechanisms are likely to realize a narrower share of the innovation benefits documented in this chapter, and to bear a correspondingly larger share of the associated risks.

9. Conclusion

This chapter has argued that Generative AI is best understood not as a replacement for human innovators but as an active co-creator whose value emerges from its complementarity with human expertise, creativity, judgment, and contextual understanding. Three central messages summarize this argument. First, GenAI can contribute meaningfully across multiple stages of the innovation process, from opportunity recognition and idea generation through evaluation, development, business model innovation, commercialization, and organizational innovation, as documented throughout Section 4. Second, the greatest value from this technology is likely to emerge not from replacing human contributors but from deliberately combining human and AI capabilities within an iterative co-creation cycle, as set out in Sections 5 and 7—provided that organizations also attend to the reliability, bias, intellectual property, over-reliance, and governance challenges reviewed in Section 6. Third, and looking forward, innovation management can increasingly be conceptualized around a simple but consequential formula: Human + GenAI → Co-Created Innovation. Realizing this potential will depend less on the continued technical advancement of generative models themselves than on how deliberately organizations design the human–AI co-creation processes, capabilities, and governance structures through which that potential is put into practice.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, ChatGPT was used for language editing and proofreading to improve the clarity and readability of the chapter. Claude was used to assist with model visualization, and Elicit was used to support the literature search and identification of relevant academic publications. The author reviewed the outputs generated by these tools and remains responsible for the final content of the chapter.

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Chapter 7:

Perceived Functional and Emotional Value as Drivers of Technological Innovativeness in Technology-Intensive Products

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Abstract

More advanced products do not automatically make users more willing to try new technologies. This study looks at how perceived functional value and perceived emotional value relate to the propensity for technological innovation among users of technology-intensive products. Survey data were collected from 604 graduate students who actively used smartphones. Two cases with missing values were dropped, and the remaining 602 responses were analysed with multiple linear regression. Both value dimensions had positive, significant effects on users' propensity for technological innovation, although together they explained a modest share of the variance (R^2 = .087). The results suggest that openness to new technology depends on what users get out of a product as well as on what the product can technically do. Treating perceived value as an antecedent of future adoption, rather than of a single adoption decision, moves the Technology and Innovation Management literature a step past the usual acceptance-and-use models.

Keywords: technology and innovation management, technology-intensive products, perceived functional value, perceived emotional value, technological innovativeness

1. Introduction

Each new generation of technology-intensive products comes with faster hardware, more capable software and more digital functions than the last. Does this make users more willing to adopt new technologies? Not necessarily. Technically superior products often fail to produce a stronger propensity for technological innovation, and the reasons for this gap deserve more attention in Technology and Innovation Management research. Digital products succeed when users notice what a technology offers, judge it worthwhile and fit it into their daily routines, engineering quality is only part of that story (Adner, 2006, 2017; Nambisan et al., 2017; Yoo et al., 2010).

Most earlier studies have examined technology acceptance, usage intention, user satisfaction or continued use. Much less is known about how the value users see in a technology shapes their wider readiness to take up innovations. This matters because firms in technology-intensive markets need customers who will move on to the next product and the next update, beyond the one they already own (Jiang et al., 2022; Santos-Vijande et al., 2022).

Perceived value offers a useful point of departure here. Functional value reflects the way users assess a product's performance and its practical usefulness. Emotional value, in turn, concerns the experiential and psychological bonds that users develop with a technology. Considering these two aspects side by side helps to explain why some users embrace technological innovation more readily than others (Beaudry & Pinsonneault, 2010; Sheth et al., 1991; Woodruff, 1997).

Taking smartphones as its empirical setting, this study examines the extent to which perceived functional value and perceived emotional value affect users' propensity for technological innovation. Perceived value is seen here as more than a predictor of present use; it is also treated as something that shapes how willing users are to accept innovations in the future. Previous research on value-based adoption has generally concentrated on a single, specific technology or service (a new platform,

an application, a type of service) at a given moment. This study, by contrast, understands the propensity for technological innovation as a relatively stable, future-oriented disposition: a willingness to keep taking part in an ongoing flow of change, such as new devices, new features and updates. The distinction suits smartphones particularly well. Unlike many settings that involve just one technology, the smartphone belongs to an ecosystem that never stops changing, so users are repeatedly confronted with adoption decisions.

2. Conceptual Framework

2.1. Technology-Intensive Products from a Technology and Innovation Management Perspective

From a Technology and Innovation Management (TIM) perspective, a smartphone is better understood as a technology-intensive digital system than as an ordinary consumer product. Its hardware, software, connectivity and data are bound up with a much larger innovation ecosystem, one that includes platform owners, app developers, component suppliers and network operators, along with a steady flow of software updates. How a smartphone performs in the market therefore has as much to do with its place in this ecosystem as with the quality of its engineering. Studies of digital innovation describe such products as modular and layered, not as self-contained artifacts. Their commercial success depends on many interdependent actors working in step, and in the end on whether users are able to see and use the value that this ecosystem produces (Adner, 2006, 2017; Nambisan et al., 2017; Porter & Heppelmann, 2014; Yoo et al., 2010).

The smartphone is a particularly clear case. It is never finished: new chipsets, sensors, interfaces and AI features arrive regularly, and operating system updates keep changing what an existing device can do. A good part of its value, moreover, comes from outside the device, from the services and software people use on it. Adoption also involves a trade-off between

the new and the familiar. Even a technically superior feature may be resisted if it feels unfamiliar to users or lacks adequate software support. For manufacturers, this means that better specifications alone will not carry an innovation. Users have to see it as useful and worth the effort of adopting (Lu et al., 2026; Wang et al., 2022; Zhang et al., 2026).

This study therefore treats perceived value as the link between what a technology can do and whether it is actually adopted, rather than simply as an outcome of marketing. Innovation management research has long recognized that technical superiority on its own seldom secures market acceptance. A firm can build technological potential, but that potential turns into adoption only when users see real value in it and decide to explore, adopt and use the new technology in everyday life. Functional and emotional value are examined in this light, as two routes through which a smartphone's innovative potential can either encourage or hold back users' technological innovativeness (Wang et al., 2022; Woodruff, 1997; Zeithaml, 1988; Zheng et al., 2025).

2.2. Perceived Functional Value

For technology-intensive products, perceived functional value means more than a simple judgement of usefulness. It reflects how well, in the user's eyes, a product's technical architecture delivers performance, reliability, ease of use and efficiency. Classical value theories describe value as a trade-off between benefits and costs. Technology adoption research adds that perceived usefulness and perceived ease of use are the main mechanisms through which technical features become behavioral intentions. The functional value of a smartphone is therefore not a matter of how many functions it has. What matters, then, is whether users feel that these functions help them get things done. A good interface and reliable performance are part of this, as is a phone that fits into daily routines without making technology feel more complicated than it needs to be (Davis, 1989; Sheth et al., 1991; Venkatesh et al., 2003, 2012; Woodruff, 1997; Zeithaml, 1988).

For innovation management the point is significant, because firms frequently bring out innovations faster than users can take them in. Building a new function solves only part of the problem; people still have to understand it, learn how to use it and make it part of their habits. Recent research on digital devices shows that innovations are rated more favourably when new technology is paired with familiar design principles and software that is intuitive to use. Research on mobile usability leads to a similar conclusion. Complexity can feel like a benefit or like a burden, and which of the two it becomes depends mostly on how effective, operable and easy to understand users find an application. Performance, interface quality, system stability and smooth integration thus sit at the heart of a smartphone's functional value and influence how users evaluate technological innovation (Huang & Benyoucef, 2026; Lu et al., 2026; Zhang et al., 2026).

The influence of functional value is not limited to the moment of first use. In digital services and mobile applications, it supports people's immediate intention to use a technology and gradually adds to the value they get from it over a longer period. Studies report that perceived value mediates the relationship between discoverability and adoption. They also show that functional value raises engagement and continued use, because it makes the experience more enjoyable and more rewarding in social terms. Functional value should therefore be regarded as more than a utilitarian attribute. Technological solutions create value partly through it, since it provides users with operational reliability and reduces the uncertainty they face when adopting something new (Blut et al., 2024; Jiang et al., 2022; Santos-Vijande et al., 2022; Sweeney & Soutar, 2001).

2.3. Perceived Emotional Value

Where functional value concerns what a technology allows users to do, emotional value concerns how it makes them feel and what kind of person it lets them be. This distinction is important in Technology and Innovation Management. Digital products compete on technical performance, but they also compete through the meanings attached to them, the experiences they provide and the identities users express

through them. A smartphone stays with its owner for most of the day. Its value therefore goes beyond efficiency: people enjoy using it, it gives them a sense of control, they appreciate how it looks, and it becomes a means of symbolic self-expression and an object of emotional attachment. None of this is a secondary or irrational add-on to technological utility. It is a large part of how people experience digital innovation and make sense of it (Hirschman & Holbrook, 1982; Holbrook, 1999; Wang et al., 2022).

Research on hedonic information systems and user experience makes clear that accepting a technology involves feelings as well as cognitive judgement. If using a technology is enjoyable, engaging, attractive or personally meaningful, people tend to explore its new functions, stay with it and work it into their routines. Studies of emotions in information technology adoption reach a similar conclusion, showing that emotional responses accompany use and also shape it. In technology-intensive settings, emotional value reduces the psychological distance between user and innovation. The technology no longer feels external or complicated; it becomes part of ordinary experience (Beaudry & Pinsonneault, 2010; Hassenzahl & Tractinsky, 2006; van der Heijden, 2004).

Studies of emotional attachment to mobile devices, smartphones especially, support this argument. Early work showed how the mobile phone turned into a tool for staying permanently in touch. Its emotional value came from a feeling of closeness to others, from the anxiety people felt when separated from it and from the symbolic role it played in their social relationships. More recent research goes as far as calling the smartphone a "significant other" and connects attachment to the device with interpersonal dependency and attachment patterns. Product attachment research adds that functionality and appearance both strengthen the emotional bond between user and product, which means the technical and the emotional cannot really be separated. In the case of smartphones, emotional value develops out of enjoyment and attachment, and out of the symbolic meaning the device carries and its role in how users construct their identity (Gritti et al., 2023; Mugge et al., 2010; Vincent, 2006).

Recent studies of digital technologies and augmented reality (AR) point in the same direction. Emotionally engaging experiences, including telepresence, flow, immersion and rich customer experiences, encourage continued use and greater openness to innovative applications. Read alongside research on product meaning in digital innovation, these findings suggest that emotional value is how digital products come to matter personally. Once a technology means something to users, adoption barriers are easier to overcome, because users see it as part of their own technological experience and not as a bundle of technical features (Santos-Vijande et al., 2022; Song et al., 2025; Wang et al., 2022).

2.4. Technological Innovativeness

In this study, technological innovativeness is defined as users' innovative orientation toward new technological solutions, rather than in terms of traditional consumer behavior. It refers to a relatively stable tendency to notice, evaluate, try, adopt and integrate technological innovations into one's own practices. From the standpoint of diffusion of innovations theory, this tendency is a micro-level precondition for diffusion: new solutions move from technical feasibility to wide use only if some users adopt them early. Technological innovativeness is therefore broader than wanting the latest device. It includes experimenting, learning, coping with uncertainty and accepting technological change (Agarwal & Prasad, 1998; Venkatesh et al., 2012).

This is especially true of smartphones, which go through continuous incremental and architectural innovation. Users do not make one adoption decision. They make a long series of small ones: trying a new application, moving to a new device, testing artificial intelligence features, changing how they interact with a platform, installing an update. Openness to technological innovation can thus be read as a willingness to move along with a product's technological path. The concept is closely related to personal innovativeness in the domain of information technology, technology readiness and motivated consumer innovativeness. Each of these describes a user's inner tendency to take part in technological change

actively instead of receiving it passively (Parasuraman, 2000; Parasuraman & Colby, 2015).

Openness to innovation cannot be taken for granted, however. Passive innovation resistance and barriers specific to a given innovation can weaken both adoption intentions and actual innovative behavior. Studies of smartphone users show that people may reject innovative digital solutions even when they have access to the technology, because of a mix of functional barriers, perceived utility, perceived hedonism, complexity and a general tendency to resist innovation. The propensity for technological innovation is best seen as the result of a tension between value drivers and resistance barriers. Perceived value matters strategically within this tension, since it can make an innovation feel meaningful and useful or leave it looking like an uncertain risk (Heidenreich & Kraemer, 2015).

2.5. Developing a Hypothesis on the Effect of Perceived Functional Value

The expectation is that perceived functional value will increase the propensity for technological innovation, since it makes the practical benefits of an innovation easier for users to see. Newness or technical sophistication rarely wins users over on its own. People turn to a technology when it proves useful, is easy to learn and helps with problems they really have. Research based on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and perceived value supports this view. It shows that perceived usefulness and ease of use reduce cognitive uncertainty, and that performance expectancy and value perceptions have the same effect; together, they make users more confident about adopting new technologies (Davis, 1989; Venkatesh et al., 2003, 2012; Zeithaml, 1988).

The smartphone is a good example. Recent research on digital devices finds that users react more positively to an innovation when it mixes the new with the familiar, and when software support lets new functions blend into the experience users already have. Mobile usability

studies trace favorable evaluations of mobile technologies back to perceived ease of use and effectiveness. Work on digital services and mobile applications adds that perceived value encourages adoption and that functional value later strengthens engagement. A phone with high perceived functional value therefore offers its user more than technical superiority. Once users notice how innovations improve their interactions in digital settings, they tend to conclude that adopting technological innovations in general is worthwhile (Huang & Benyoucef, 2026; Jiang et al., 2022; Lu et al., 2026; Santos-Vijande et al., 2022; Zhang et al., 2026).

A broader argument in innovation management points in the same direction, namely that technological opportunities produce value only when users can recognize them and put them to use. Users who consistently find their smartphone reliable, useful, well made and technically advantageous are more inclined to treat the next innovation as an improvement. It makes little difference whether that innovation is a new device, a software update, a digital service or an extra function. In each case, it is less likely to be resisted as a threat to familiar routines. Perceived functional value raises the propensity for technological innovation precisely because it changes how technological change is perceived, making it appear as a visible improvement in the user experience rather than a source of uncertainty (Blut et al., 2024; Corrocher & Paganuzzi, 2025; Zheng et al., 2025).

On this basis, the following hypothesis is proposed:

H_1: Perceived functional value has a positive effect on the propensity for technological innovation.

2.6. Developing a Hypothesis on the Effect of Perceived Emotional Value

A similar effect is expected from perceived emotional value, though it operates differently. Where functional value reduces uncertainty by showing users what an innovation can practically do for them, emotional value acts through engagement, personal meaning and the feeling of being close to a technology. Users who take pleasure in their smartphones, or

who see them as meaningful and as part of the way they present themselves to others, generally show more willingness to explore new functions. For them, a new feature is less a technical change than a continuation of an experience they already value (Hirschman & Holbrook, 1982; Holbrook, 1999; van der Heijden, 2004).

This reasoning finds support in research on emotions and user experience in information technology. Emotions shape technology use in direct as well as indirect ways. Pleasant interactions and hedonic qualities encourage people to keep using a technology, and they also make people more open to trying out new features. Studies of smartphone attachment show that the device can become an important relational object for its owner. Users who are more strongly attached to it interact with it more and are keener to maintain the relationship. Recent work on digital product innovation makes an additional observation: the meanings people assign to digital products are part of the innovation process itself, and do not simply result from marketing communication. In this light, emotional value can be treated as a strategic resource that helps users accept new technologies and build them into their identities and everyday lives (Beaudry & Pinsonneault, 2010; Gritti et al., 2023; Mugge et al., 2010; Vincent, 2006; Wang et al., 2022).

Evidence from augmented reality and mobile application research strengthens the argument. Emotionally engaging digital experiences have been found to improve user retention, and individual innovativeness increases the positive effects of immersive technologies. For this study, the implication is that emotional value adds to functional value instead of substituting for it. Because it stimulates curiosity, exploratory behavior and intrinsic motivation, emotional value makes users actively want technological innovation instead of merely putting up with it. The smartphone market changes continuously, and in such a setting perceived emotional value can be expected to act as an important antecedent of the propensity for technological innovation. It helps users keep pace with the changes that keep coming (Santos-Vijande et al., 2022; Song et al., 2025).

On this basis, the following hypothesis is proposed:

H_2: Perceived emotional value has a positive effect on the propensity for technological innovation.

3. Methodology

3.1. Research Design

The study used a quantitative, explanatory, cross-sectional design. A quantitative approach made it possible to measure the relationships between the model's variables with numerical data and to test the hypotheses statistically. The design is explanatory because it examines the effects of perceived functional and emotional value on consumers' propensity for technological innovation, and cross-sectional because all data were collected at one point in time. The hypotheses were tested with survey data, and the research model was analysed using multiple linear regression.

3.2. Research Model

The conceptual model draws on theoretical work in Technology and Innovation Management that explains how perceived value influences consumer behavior. Perceived functional value and perceived emotional value are the independent variables, and the propensity for technological innovation is the dependent variable. The model is designed to examine how the two value dimensions influence consumers' propensity for technological innovation in the context of technology-intensive products. Figure 1 shows the proposed relationships.

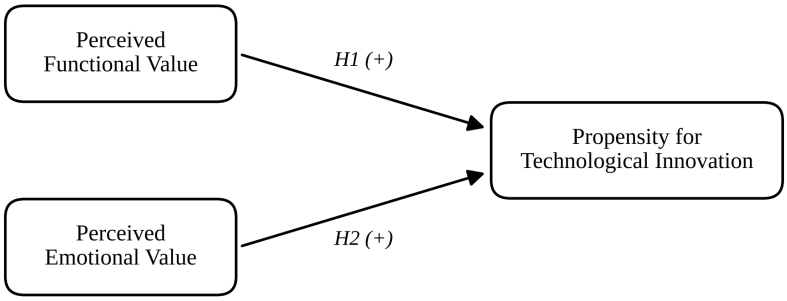


Figure 1. Research Model

3.3. Research Hypotheses

Following the model in Figure 1, the study tests the two hypotheses developed in Section 2 (H_1 and H_2) on the effects of perceived functional and emotional value on the propensity for technological innovation.

3.4. Population and Sample

The target population was graduate students at Istanbul Beykent University. The required sample size was calculated with the formula below, assuming a 95% confidence level and a ±4% margin of error (Yükselen, 2017):

$$n = p \times q \times (Z/e)^2$$

where $p = .50$, $q = .50$, $Z = 1.96$, and $e = \pm.04$.

$$n = .50 \times .50 \times (1.96/.04)^2 \approx 600 \text{ participants}$$

With these parameters ($p = .50$, $q = .50$, $Z = 1.96$, $e = \pm.04$), the minimum sample size came to 600 participants. Data collection produced 604 valid questionnaires. Two items had one missing response each (KAL5 and DUYDER2), and the two cases concerned were removed by listwise deletion. The exploratory factor analysis (EFA), reliability analysis, confirmatory factor analysis (CFA), correlation analysis and multiple

regression analysis were therefore all run on $n = 602$, which still meets the calculated minimum.

Participants were reached through convenience sampling. Graduate students were chosen because they use smartphones heavily for study, work, communication and everyday tasks and have enough experience to compare different technological options. They can judge both the functional features of their phones and the emotional benefits of using them, which makes them a suitable group for studying perceived functional value, perceived emotional value and the propensity for technological innovation. Students were drawn from several graduate programs to increase variety in educational background, occupation and user experience. Only responses from active smartphone users were included in the final analysis.

3.5. Data Collection Process and Measurement Instruments

The data come from a structured questionnaire. Before taking part, respondents were informed about the aim of the study, and participation was entirely voluntary. The questionnaire was given only to active smartphone users, and forms that were incomplete or filled in incorrectly were not used. Screening left 604 valid questionnaires. Two of these had a missing response on a scale item and were dropped, so the analyses that follow are based on 602 cases.

To measure perceived value, the scale developed by Tümen (2011) was adapted. Of its dimensions, we kept perceived functional value and perceived emotional value, each measured with five items; monetary value was not included, as it had no direct bearing on the research question. The propensity for technological innovation was measured with a scale adapted from Suh and Yi (2006), which originally contained three items. In the exploratory factor analysis (EFA), one of these items loaded on more than one factor, so it was removed and two items were retained. Responses to all items were given on a five-point Likert scale, with 1 meaning “Strongly disagree” and 5 meaning “Strongly agree”.

Because the scales were used in a new sample, their validity and reliability were checked again. This involved an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA), as well as the calculation of Cronbach's alpha, composite reliability (CR), average variance extracted (AVE) and the heterotrait–monotrait ratio (HTMT). These results are presented in the Findings section.

The survey was conducted in 2016, some years before the present manuscript was prepared, and this gap may be regarded as a limitation. Perceived functional value, perceived emotional value and technological innovativeness are, however, fairly stable psychological and behavioral tendencies. They do not depend on a particular generation of devices or a specific software version, which is why the findings can still be considered relevant. The conceptual framework, the literature review, the hypotheses and the analytical approach have all been revised in light of recent research in Technology and Innovation Management so that the study reflects the current state of the field.

3.6. Data Analysis

All analyses were carried out in Python. The dataset was first checked for missing values, data entry errors and outliers. The two cases with missing responses on scale items were removed listwise, and every analysis was run on $n = 602$. Frequencies, percentages, means and standard deviations were used to describe the participants' demographic characteristics and the research variables.

Exploratory factor analysis (EFA) was used first to assess construct validity. Sampling adequacy was checked with the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Once the factor structure was established, internal consistency was assessed with Cronbach's alpha.

The structure from the EFA was then tested with confirmatory factor analysis (CFA). Convergent validity was evaluated with composite reliability (CR) and average variance extracted (AVE), and discriminant validity with the heterotrait–monotrait ratio (HTMT). Pearson correlations were computed to describe the linear relationships among the

variables, and the hypotheses were tested with multiple linear regression. The main regression assumptions (normality of residuals, homoscedasticity, independence of errors, multicollinearity and influential observations) were also checked. Because the homoscedasticity tests gave mixed results, the coefficients were re-estimated with heteroscedasticity-consistent (HC3) standard errors (Long & Ervin, 2000). The significance level was set at $p < .05$. Since all constructs came from the same self-report questionnaire administered at one time, Harman's single-factor test was used to look for possible common method bias.

4. Findings

4.1. Demographic Characteristics of the Participants

Table 1 summarises the participants' demographic characteristics. Of the 602 respondents in the analytic sample, 54.5% were female (n = 328) and 45.5% male (n = 274). By age, 34.9% were 20–25, 30.1% were 26–30, 22.4% were 31–35, and 12.6% were 36 or older. The sample thus covers users of technology-intensive products from several age groups and both genders.

Table 1. Demographic characteristics of the participants (n = 602)

Variable	Category	*n*	%
Gender	Male	274	45.5
	Female	328	54.5
Age	20–25	210	34.9
	26–30	181	30.1
	31–35	135	22.4
	36 or older	76	12.6

4.2. Exploratory Factor Analysis

Exploratory factor analysis (EFA) was used to assess the construct validity of the scales. The analysis was run in Python with the factor_analyzer library, using minimum residual (minres) extraction and Varimax orthogonal rotation. Before the analysis, the suitability of the data

was checked with the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity.

All 13 items were entered at first. Item IMAJ3 loaded at similar levels on two factors (.425 and .409). Because cross-loading items weaken construct validity, it was dropped and the EFA was repeated with the remaining 12 items.

The final analysis used data from the 602 participants without missing values, the same sample used in all later analyses. The KMO value was .890, and Bartlett's test was significant ($\chi^2(66) = 5493.87$, $p < .001$), so the data were suitable for factor analysis.

After Varimax rotation, a three-factor structure emerged that matched the theoretical model. Loadings ranged from .751 to .852 for perceived emotional value, from .702 to .826 for perceived functional value and from .735 to .985 for the propensity for technological innovation. The three factors together explained 72.6% of the total variance. With all loadings above the recommended threshold and a satisfactory level of explained variance, the three-dimensional structure supports the theoretical model and shows adequate construct validity.

Table 2. Final exploratory factor analysis results (n = 602, minres, varimax)

Item	Perceived Emotional Value	Perceived Functional Value	Propensity for Technological Innovation
DUYDER1	.783		
DUYDER2	.852		
DUYDER3	.820		
DUYDER4	.827		
DUYDER5	.751		
KAL1		.758	
KAL2		.826	
KAL3		.702	
KAL4		.807	
KAL5		.765	

CTILG8	.985
CTILG9	.735

Note: KMO measure of sampling adequacy = .890, Bartlett's test of sphericity: $\chi^2(66) = 5493.87$, $p < .001$, total variance explained = 72.6%. Loadings below .40 are not shown.

4.3. Reliability Analysis

Cronbach's alpha was then calculated to assess internal consistency. Values of .70 or higher are generally taken to indicate acceptable reliability (Hair et al., 2019; Kline, 2023).

Alpha was .913 for perceived functional value, .934 for perceived emotional value and .860 for the propensity for technological innovation. All three exceed the threshold, so the scales show high internal consistency. Table 3 reports the results.

Table 3. Reliability analysis results ($n = 602$)

Dimension	Number of Items	Cronbach's Alpha
Perceived Functional Value	5	.913
Perceived Emotional Value	5	.934
Propensity for Technological Innovation	2	.860

4.4. Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was then run on the 602 observations to test the measurement model. It was estimated in Python with the *semopy* library using maximum likelihood. Standardized loadings ranged from .768 to .898, and every item represented its latent variable adequately (see Table 5). The propensity for technological innovation construct was left with two items after the cross-loading item was removed at the EFA stage. Both items still loaded strongly (.851–.886), and the construct reached satisfactory composite reliability (CR = .860) and average variance extracted (AVE = .755), so the shorter item set appears to measure the construct adequately.

Model fit was judged on several types of indices rather than on any single one (Hu & Bentler, 1999; Kline, 2023). The values were: $\chi^2(51) = 318.01$, $p < .001$, $\chi^2/df = 6.24$, CFI = .951, TLI = .937, GFI = .943, AGFI = .926, NFI = .943, RMSEA = .093 (90% CI [.084, .103]), SRMR = .035. SRMR is well under the ≤ .08 cut-off for good fit, and CFI is above the ≥ .95 cut-off (Hu & Bentler, 1999). TLI, GFI, AGFI and NFI meet the ≥ .90 criterion for acceptable fit (Schermelleh-Engel et al., 2003). The χ^2/df ratio of 6.24, on the other hand, is above both the ≤ 3 criterion (Schermelleh-Engel et al., 2003) and the more lenient ≤ 5 limit used by some authors (Marsh & Hocevar, 1985). The chi-square statistic is sensitive to sample size and tends to inflate this ratio in large samples (Kline, 2023), but the value should still be read as a sign of poor fit. RMSEA (.093) falls in the "mediocre" range (.08–.10) in MacCallum et al.'s (1996) classification, and the upper limit of its confidence interval (.103) is slightly above .10. In short, fit is acceptable on the incremental and residual-based indices but only mediocre on χ^2/df and RMSEA. No error covariances were added, since there was no theoretical reason for them and adding them would only have fitted the model to this sample. The issue is taken up again in the limitations. Table 4 lists the fit indices.

Standardized loadings ranged from .768 to .878 for perceived functional value, from .821 to .898 for perceived emotional value and from .851 to .886 for the propensity for technological innovation. All loadings exceed the recommended threshold, so the observed variables represent their latent constructs adequately. The factor structure supports the theoretical model, but the overall fit of the measurement model should be interpreted cautiously given the limitations noted above.

Table 4. Confirmatory factor analysis fit indices (n = 602)

Index	Value	Criterion (source)	Result
χ^2/df	6.24	≤ 2 good, ≤ 3 acceptable (Schermelleh-Engel et al., 2003), lenient criterion ≤ 5 (Marsh & Hocevar, 1985)	Above thresholds
CFI	.951	≥ .95 good, ≥ .90 acceptable (Hu & Bentler, 1999)	Good fit
TLI	.937	≥ .95 good, ≥ .90 acceptable (Hu & Bentler, 1999)	Acceptable
GFI	.943	≥ .95 good, ≥ .90 acceptable (Schermelleh-Engel et al., 2003)	Acceptable
AGFI	.926	≥ .90 good, ≥ .85 acceptable (Schermelleh-Engel et al., 2003)	Good fit
NFI	.943	≥ .95 good, ≥ .90 acceptable (Schermelleh-Engel et al., 2003)	Acceptable
RMSEA [90% CI]	.093 [.084, .103]	≤ .05 good, .05–.08 acceptable, .08–.10 mediocre, > .10 poor (MacCallum et al., 1996)	Mediocre
SRMR	.035	≤ .08 good (Hu & Bentler, 1999)	Good fit

Note: $\chi^2(51) = 318.01$, $p < .001$. CI = confidence interval.

Table 5. Standardized factor loadings from the confirmatory factor analysis

Dimension	Item	Standardized Factor Loading
Perceived Functional Value	KAL1	.810
	KAL2	.878
	KAL3	.768
	KAL4	.831
	KAL5	.834
Perceived Emotional Value	DUYDER1	.841
	DUYDER2	.898
	DUYDER3	.869
	DUYDER4	.870
	DUYDER5	.821
Propensity for Technological Innovation	CTILG8	.886
	CTILG9	.851

Note: All loadings are significant at $p < .001$.

4.5. Convergent and Discriminant Validity

Convergent and discriminant validity were assessed next. For convergent validity, composite reliability (CR) and average variance extracted (AVE) were used, CR above .70 and AVE above .50 are the usual benchmarks (Fornell & Larcker, 1981; Hair et al., 2019).

Perceived functional value had CR = .914 and AVE = .681, perceived emotional value had CR = .934 and AVE = .740, and the propensity for technological innovation had CR = .860 and AVE = .755. All values exceed the benchmarks, so convergent validity is supported.

Discriminant validity was assessed with the heterotrait–monotrait ratio (HTMT). Values below .85 (strict criterion) or .90 (lenient criterion) indicate that constructs are sufficiently distinct (Henseler et al., 2015). The HTMT values ranged from .287 to .631, all below both thresholds. Convergent and discriminant validity are therefore both supported. Table 6 presents the results.

Table 6. Convergent and discriminant validity results

Panel A. Reliability and Convergent Validity			
Construct	**Cronbach's Alpha**	**CR**	**AVE**
Perceived Functional Value	.913	.914	.681
Perceived Emotional Value	.934	.934	.740
Propensity for Technological Innovation	.860	.860	.755
Panel B. HTMT Values			
Constructs	**Functional**	**Emotional**	**Technological Innovation**
Functional	—		
Emotional	.631	—	
Technological Innovation	.301	.287	—

Note: The results of Harman's single-factor test for common method bias are reported separately in Section 4.9.

4.6. Descriptive Statistics and Correlation Analysis

Table 7 gives the descriptive statistics and Pearson correlations. Mean scores were 3.838 (SD = 0.937) for perceived functional value, 3.815 (SD = 1.007) for perceived emotional value and 3.320 (SD = 1.299) for the propensity for technological innovation.

Perceived functional value and perceived emotional value were moderately and positively correlated (r = .582, p < .001). The propensity for technological innovation was positively and significantly correlated with perceived functional value (r = .267, p < .001) and with perceived emotional value (r = .257, p < .001).

All correlations run in the expected direction, which provides a sound basis for the regression analysis.

Table 7. Descriptive statistics and correlation analysis (n = 602)

Variable	*M*	*SD*	1	2	3
1. Perceived Functional Value	3.838	0.937	—		
2. Perceived Emotional Value	3.815	1.007	.582***	—	
3. Propensity for Technological Innovation	3.320	1.299	.267***	.257***	—

***p < .001.

4.7. Hypothesis Testing

The hypotheses were tested with multiple linear regression. The model as a whole was significant (F(2, 599) = 28.48, p < .001) and explained 8.7% of the variance in the propensity for technological innovation (R^2 = .087, adjusted R^2 = .084).

Perceived functional value had a positive and significant effect on the propensity for technological innovation (B = 0.245, SE = 0.067, β = .177, t = 3.68, p < .001), so H_1 is supported.

Perceived emotional value also had a positive and significant effect (B = 0.199, SE = 0.062, β = .155, t = 3.22, p = .001), so H_2 is supported as well. Both effects stayed significant with heteroscedasticity-consistent (HC3) standard errors (functional value: t = 3.41, p < .001, emotional value: t = 2.94, p = .003). The standardized coefficients show that the two effects are small and of similar size. Full results are given in Table 8.

Table 8. Regression analysis results for hypothesis testing (n = 602)

Independent Variable	*B*	*SE*	β	*t*	*p*	95% CI (*B*)
Constant	1.620	0.231	—	7.01	< .001	[1.167, 2.074]
Perceived Functional Value	0.245	0.067	.177	3.68	< .001	[0.114, 0.375]
Perceived Emotional Value	0.199	0.062	.155	3.22	.001	[0.078, 0.321]

Note: Dependent variable: Propensity for Technological Innovation. B = unstandardized coefficient, SE = standard error, β = standardized coefficient, CI = confidence interval. R^2 = .087, adjusted R^2 = .084, $F(2, 599) = 28.48$, p < .001. H_1 and H_2 are supported.

4.8. Testing the Assumptions of the Regression Model and Diagnostics

The main assumptions of multiple linear regression were checked through residual analysis and diagnostic statistics (Hair et al., 2019).

Multicollinearity: The variance inflation factor (VIF) was 1.51 and tolerance was .66 for both perceived functional value and perceived emotional value. These values meet the usual criteria (VIF < 10, tolerance > .10) (Hair et al., 2019), so multicollinearity is not a concern.

Normality of residuals: Residual skewness (−0.38) and kurtosis (−0.76) were within ±1. The Shapiro–Wilk test did indicate a significant departure from normality (W = .966, p < .001), but this test is known to flag even small deviations in large samples. With n = 602, the departure is unlikely to affect the coefficient estimates in any meaningful way (Hair et al., 2019).

Homoscedasticity: The Breusch–Pagan test found no heteroscedasticity ($\chi^2(2) = 1.03$, $p = .598$), whereas the more general White test was marginally significant ($\chi^2(5) = 12.20$, $p = .032$). The model was therefore re-estimated with HC3 heteroscedasticity-consistent standard errors (Long & Ervin, 2000), and both coefficients remained significant (Section 4.7).

Independence of errors: The Durbin–Watson statistic was 1.62, inside the commonly accepted range of 1.5 to 2.5.

Linearity and influential observations: The Ramsey RESET test was marginally significant ($F(1, 598) = 4.19$, $p = .041$). The added nonlinear term explained only about 0.6% more variance, however, so the linear model was kept. No standardized residual lay outside ±3, and the largest Cook's distance was .035 (< 1), so no single observation had an undue influence on the results.

Overall, the diagnostics suggest that the regression estimates can be relied on. The small departures from normality and homoscedasticity did not change the results once robust estimates were used.

4.9. Common Method Bias

All constructs were measured with the same self-report questionnaire at a single point in time, so common method bias (CMB) is a possible concern (Podsakoff et al., 2003). Harman's single-factor test was used to assess it: the 12 items of the final measurement model were entered into an unrotated principal component analysis. The first component (eigenvalue = 6.28) accounted for 52.3% of the total variance. This is above the 50% level often used as a warning sign, so common method variance may have influenced the observed relationships to some degree, and the result should be read with caution. Harman's test is also a blunt instrument. Its sensitivity is limited, and on its own it can neither confirm nor rule out common method bias (Fuller et al., 2016; Podsakoff et al., 2003).

The HTMT results in Section 4.5 address a separate question. Because all HTMT values (.287–.631) are below .85, the three constructs can be told apart empirically, which establishes discriminant validity (Henseler et al., 2015). HTMT does not, however, measure common method bias directly, and good discriminant validity should not be taken as evidence that such bias is absent.

Given the single-source, cross-sectional design, the possibility of common method variance cannot be excluded, and the strength of the reported relationships should be interpreted with this in mind. The Conclusion returns to this limitation and to the need for designs that separate the measurement of predictor and criterion variables in time or by procedure.

5. Discussion

The overall picture is consistent. For technology-intensive products, both perceived functional value and perceived emotional value are positively related to users' propensity for technological innovation. This is easy to miss in a market that competes on specification sheets and feature lists: technical superiority does not guarantee that users will take up what a product offers. The value users actually experience when they use the technology seems to matter more. The result agrees broadly with earlier work on perceived value and technology acceptance (Davis, 1989; Sheth et al., 1991; Venkatesh et al., 2003; Venkatesh et al., 2012) and with more recent studies (Kowalczuk & Hof, 2025; Lee & Yoon, 2025). What this study adds is a step further in the same logic. Perceived value is shown to explain whether a person adopts one particular technology and, beyond that, how willing they are to keep up with future technological change.

The size of the effects needs to be stated plainly. The two value dimensions explained only 8.7% of the variance in the propensity for technological innovation ($R^2 = .087$), and the standardized coefficients ($\beta = .177$ and $\beta = .155$) point to small effects. Much of what drives users' openness to innovation clearly lies outside this model. Perceived social value, technology readiness and individual innovativeness are obvious

candidates for future studies. On the other hand, the sample was large (n = 602), the effects held up with robust standard errors and their direction matched theoretical expectations. Taking into account the possibility of common method variance and the mediocre fit of the measurement model (Sections 4.4 and 4.9), the findings are best seen as one meaningful piece of a larger picture, to be interpreted with some caution.

The positive effect of perceived functional value suggests that users judge new technologies first in practical terms: what will this actually do for me? This matches the perceived usefulness construct of the Technology Acceptance Model (Davis, 1989) and performance expectancy in UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012). It also fits more recent work that puts performance, ease of use and functional utility at the center of how users evaluate technology (Lee & Yoon, 2025; Shen et al., 2026; Wang et al., 2022). Earlier studies mostly stopped at acceptance, purchase intention or continued use. Here, functional value is also linked to users' general openness to innovation. It seems to do more than switch technology use on, it helps make people willing to adopt whatever comes next.

Perceived emotional value adds a complementary explanation. Its positive, significant effect shows that technology use is seldom a purely rational weighing of costs and benefits. The feelings and personal meanings people attach to their devices matter as well. This is consistent with the emotional value dimension of the Theory of Consumption Values (Sheth et al., 1991), with the PERVAL model (Sweeney & Soutar, 2001) and, more broadly, with research on user experience and hedonic motivation (Beaudry & Pinsonneault, 2010; Hassenzahl & Tractinsky, 2006). Recent studies of emotional attachment to smart devices point the same way (Kowalczuk & Hof, 2025; Shen et al., 2026). The pattern is not the same for every technology, though. In their study of AI-based digital humans, Tang and Son (2025) found that functional value counted for relatively little and that cognitive and emotional value did most of the work. The relative weight of functional and emotional value probably depends on the kind of technology involved. With something as

embedded in daily life as a smartphone, the two seem to work side by side, while for more experience-driven technologies emotional value may weigh more heavily. Either way, the present findings suggest that emotional value affects how open people stay to future technologies, and not just how they use technology now.

More generally, the results cannot be explained by technical features alone. Whether a technological innovation succeeds seems to depend less on its raw potential than on the value users get from it. This fits the digital innovation literature, which sees innovation as emerging from the interaction of technology, users and value creation (Nambisan et al., 2017; Yoo et al., 2010). Recent work on technology-intensive markets also observes that competitive advantage increasingly comes from value created through user experience (Ferreira et al., 2025; Ray et al., 2026), and the present results are in line with that view.

The study makes three contributions. It brings perceived functional value and perceived emotional value into one model as antecedents of technological innovativeness instead of examining them separately. It shows that the reach of perceived value extends past acceptance and use to users' wider openness to future innovations. And it offers a more integrated view of Technology and Innovation Management, in which lasting success depends on turning advanced technologies into products users find meaningful, useful and emotionally engaging, as well as on building those technologies in the first place.

6. Conclusion

Users' propensity for technological innovation in technology-intensive products depends, significantly but modestly, on the value they perceive in those technologies. Both perceived functional value and perceived emotional value had positive, significant effects on users' openness to innovation. Technical superiority alone is not enough to secure adoption, what counts is whether users find a technology useful and meaningful and believe it can give them a good experience.

For the Technology and Innovation Management literature, the study shows that perceived value helps explain users' underlying propensity to adopt future innovations, in addition to acceptance and use. For managers of technology-intensive products, the practical message is that technological performance is not decisive on its own. Investment in the experiences and product attributes that create functional and emotional value is just as justified. In these markets, helping users recognize and feel that value appears to matter as much as building more advanced technology.

The study has several limitations. The data were collected in 2016, at a single point in time, from a convenience sample of graduate students at one university, which limits both generalisability and causal inference. All constructs were measured with the same self-report questionnaire, and the first factor in Harman's single-factor test accounted for 52.3% of the total variance, common method variance may therefore have influenced the observed relationships to some extent (Podsakoff et al., 2003). Future studies should separate the measurement of predictor and criterion variables in time or by procedure, include a marker variable or model a latent method factor. The measurement model fitted only moderately well on χ^2/df and RMSEA, and the propensity for technological innovation was measured with only two items, so the measurement results call for caution. Lastly, the model was deliberately restricted to perceived functional and emotional value as antecedents of technological innovativeness. Future research could test the same relationships for other technology-intensive product categories and in other cultural settings, ideally with longitudinal designs. The model could also be widened to include perceived social value, epistemic value, technology readiness or individual innovativeness, which would give a fuller account of what drives users' propensity for technological innovation.

Declarations

Ethics Committee Approval: The data for this study were collected in 2016 as part of the author's doctoral dissertation research. In Türkiye, the requirement for survey-based social science research to obtain institutional

ethics committee approval became binding for higher education institutions only from 2020 onwards. Because no such requirement existed at the time of data collection, no application for ethics committee approval was made for this study. Nevertheless, the study was conducted in accordance with the ethical principles of the Declaration of Helsinki: participation was voluntary, respondents were informed of the purpose of the study before participating, and all responses were collected anonymously.

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Chapter 8:

Digitalization, Bureaucracy and Merit in Public Administration: The ÇAM Digital Bureaucracy-Merit Analytical Framework

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Abstract

This chapter examines how digital transformation reshapes the relationship between bureaucracy and merit in public organizations from the perspective of middle level managers. Drawing on a qualitative study of 12 public managers, the chapter uses semi-structured interviews and thematic analysis supported by MAXQDA. The dataset contains 430 coding instances distributed across digitalization (150), merit (143), and bureaucracy (137). The findings indicate that digitalization does not eliminate bureaucratic organization. Rather, rules, hierarchy, control, record-keeping, and administrative procedures are reconfigured through digital systems. At the same time, merit is interpreted more broadly than formal education or appointment criteria, encompassing competence, experience, performance, responsibility, managerial capability, ethical judgement, and the capacity to work effectively with digital systems. Complementary Pearson correlation indicators calculated from case-level coding measures show positive associations between digitalization and merit ($r = .695$, $p = .0061$), digitalization and bureaucracy ($r = .642$, $p = .0122$), and especially bureaucracy and merit ($r = .991$, $p < .001$). These coefficients are interpreted as complementary relational indicators that inform the analysis of joint meaning-making rather than as evidence of causality. Integrating functionalist and interpretive perspectives, the chapter argues that digital transformation is better understood as a reconfiguration of the bureaucracy-merit relationship than as a transition from bureaucracy to bureaucracy-free administration. The chapter's distinctive contribution is the ÇAM Digital Bureaucracy-Merit Analytical Framework, which brings digitalization infrastructure, the integrated bureaucracy-merit dimension, algorithmic management, institutional outcomes, and environmental conditions into a single analytical field without treating these elements as a deterministic causal chain.

Keywords: digital transformation, public administration, bureaucracy-merit relationship, managerial competence, digital competence, algorithmic management, middle-level managers, qualitative research

1. Introduction

Digital transformation has become a central concern in public administration because digital technologies increasingly mediate how public organizations process information, coordinate work, exercise control, and make decisions. Yet digital transformation should not be reduced to the introduction of new software, electronic records, or automated procedures. It also changes the organizational conditions under which rules are interpreted, authority is exercised, responsibilities are allocated, and managerial competence is evaluated. This chapter therefore approaches digital transformation as an organizational and managerial process rather than as a purely technical modernization project.

One of the central questions raised by this transformation concerns the relationship between bureaucracy and merit. Bureaucracy provides a structure for authority, specialization, formal rules, documentation, accountability, and continuity. Merit concerns the principles through which people are selected, assigned responsibilities, evaluated, promoted, and trusted on the basis of relevant competence and performance. In public organizations, these dimensions are not independent institutional domains. Merit is enacted through positions, procedures, responsibilities, reporting arrangements, and decision processes that are themselves bureaucratically organized. The chapter consequently treats bureaucracy and merit as an integrated analytical dimension rather than as separate variables.

Classical bureaucratic theory provides the starting point for this argument. Weber's account of rational-legal authority identifies hierarchy, formal rules, specialization, competence, and written documentation as central characteristics of modern bureaucracy (Weber, 1978). These characteristics create predictability and organizational continuity, but they can also generate tensions when formal procedures become detached from substantive organizational purposes. Merton (1940) highlighted this problem by showing how bureaucratic structures may produce dysfunctional consequences when conformity to rules becomes an end in itself.

Digitalization adds another layer to this long-standing relationship. Information and communication technologies can strengthen standardization, traceability, and control while also changing the location and form of administrative discretion (Bovens & Zouridis, 2002). Digital systems can therefore reproduce bureaucratic principles in new technological forms rather than simply replacing bureaucracy. Cordella (2007) and Cordella and Tempini (2015) similarly show why electronic government should not automatically be understood as the disappearance of bureaucracy.

Algorithmic routines and artificial intelligence make this relationship even more consequential. Omidvar et al. (2023) demonstrate that organizations may adapt technologically while continuing to reproduce established assumptions, categories, and ways of organizing. Their concept of dynamic inertia is useful for understanding why a digital process may be faster and more traceable than a paper-based process while leaving the underlying distribution of authority and responsibility largely unchanged.

Against this background, the chapter examines how middle-level managers interpret digital transformation in relation to the integrated bureaucracy-merit dimension. Middle-level managers are particularly important because they occupy an interface position between organizational rules, senior-level decisions, professional expertise, personnel practices, digital systems, and operational realities. Their interpretations provide an empirical window into how formal structures and technological systems are experienced in everyday organizational practice.

The chapter is based on a qualitative study of 12 public managers. It uses semi-structured interviews, MAXQDA-supported thematic analysis, and complementary analysis of case-level coding relationships. The analysis does not treat digitalization, bureaucracy, and merit as independent variables in a deterministic model. Instead, it examines how these dimensions are jointly constructed in managerial accounts and how their relationships can be interpreted theoretically.

The chapter's distinctive contribution lies in bringing these elements into one analytical field. Existing discussions often examine digital government, bureaucratic transformation, managerial competence, or merit separately; the ÇAM framework instead asks how digitalization reconfigures the institutional relationship through which rules, responsibilities, competence, discretion, and accountability are enacted together. In this sense, the framework does not claim a new causal mechanism. Its contribution is analytical: it makes visible a bureaucracy-merit nexus that can otherwise remain fragmented across separate strands of public administration research.

The chapter first establishes the theoretical problem and the literature from which the integrated bureaucracy-merit perspective is developed. It then explains the qualitative design and analytical procedures, presents the empirical findings, interprets them through the functionalist-interpretive synthesis, and develops the ÇAM framework. The final sections specify the framework's theoretical, managerial, and policy implications and clarify its scope and limitations.

2. Theoretical Background

2.1. Digitalization and the Transformation of Public Administration

Digitalization in public administration involves the development and use of digital systems, data infrastructures, integrated platforms, artificial intelligence, automation, analytics, and electronic public services. Its organizational consequences, however, extend beyond technology. Digital transformation requires changes in processes, competencies, leadership practices, organizational culture, and institutional capacity. Technology is therefore better understood as an enabling infrastructure than as an autonomous explanation of organizational change. OECD (2020) similarly frames digital government as a multidimensional transformation involving digital-by-design, data-driven government, platform approaches, openness, user orientation, and proactiveness.

From a systems perspective, technology, people, data, procedures, and organizational structures form an interconnected whole (Bertalanffy, 1968). From the perspective of bounded rationality, information systems can expand decision-makers' access to information without eliminating the cognitive and organizational limits surrounding decisions (Simon, 1947). Digitalization therefore changes the conditions under which administrative decisions are produced rather than removing the need for managerial judgement.

Digital public organizations increasingly integrate technological and institutional elements. Data become organizational resources; digital records strengthen traceability; automated workflows redistribute tasks; and integrated systems connect units that previously operated through fragmented procedures. Such changes can improve efficiency and transparency, but they can also reproduce existing organizational arrangements in digital form. A paper procedure transferred into an electronic system may remain bureaucratic even when its interface is digital.

2.2. Bureaucracy, Merit, and Their Institutional Relationship

Weber's conception of bureaucracy remains a central reference point for understanding modern public organizations. Rational-legal authority is organized around formally defined competencies, hierarchical relationships, written documentation, specialized roles, and rules expected to be applied impersonally (Weber, 1978). Bureaucracy in this sense is not simply a synonym for delay or excessive paperwork. It is a form of organizational rationality seeking predictability, continuity, calculability, and orderly coordination.

The relationship between bureaucracy and competence is especially relevant to this chapter. Weberian bureaucracy assumes that office-holders occupy positions on the basis of technical qualification and that authority is attached to the office rather than to the personal characteristics of the office-holder (Weber, 1978). Merit therefore has a structural affinity with

bureaucratic organization. A bureaucratic organization requires people capable of carrying out specialized responsibilities, while a merit-oriented personnel system seeks to align appointment and progression with relevant qualifications and performance.

Merit should not be reduced to formal educational credentials. In public organizations, it can include technical knowledge, professional experience, performance, problem-solving capability, responsibility, leadership capacity, ethical judgement, and the ability to perform a role effectively (Ingraham, 1995). Peters and Pierre (2004) also demonstrate that civil-service systems remain embedded in broader questions of political control and administrative responsiveness. In the Turkish public administration literature, merit has likewise been treated as an important principle while implementation challenges continue to be identified (Yıldız, 2016).

The central theoretical point is therefore that bureaucracy and merit are mutually embedded. Bureaucracy defines positions, responsibilities, authority, procedures, and documentation; merit concerns the competence and suitability of people operating within those arrangements. The two intersect in recruitment, promotion, task assignment, performance evaluation, professional development, and everyday decision-making.

2.3. Bureaucratic Rationality, Bounded Rationality, and Managerial Judgement

Administrative decision-making is shaped by limits on human information processing. Simon's (1947) concept of bounded rationality challenged assumptions that decision-makers possess complete information and unlimited analytical capacity. Public managers make decisions within constraints created by information availability, organizational routines, time, institutional expectations, and the need to coordinate with others.

Digital systems can alter these conditions by increasing access to information and providing decision support, but they do not remove bounded rationality. A manager may possess substantial professional competence but still operate within formal authorization structures.

Conversely, a formally compliant digital system may produce consistent decisions without capturing all contextual knowledge that a competent manager considers relevant. The bureaucracy–merit relationship therefore involves an ongoing interaction between formal organizational rules and the capabilities of the people who enact them.

2.4. From Traditional Bureaucracy to Digital Bureaucracy

Digitalization changes the form through which bureaucratic principles are enacted. Paper records become electronic records; physical signatures become digital approvals; manual monitoring becomes dashboard-based monitoring; and procedural sequences may become embedded in software. These changes can reduce transaction costs and increase traceability, but they can also preserve the same underlying hierarchy and authorization logic.

Bovens and Zouridis (2002) describe a movement from street-level to system-level bureaucracy in which information technologies can relocate discretion from individual officials toward standardized systems. Cordella (2007) similarly argues that electronic government can generate an e-bureaucratic form rather than a post-bureaucratic organization. Cordella and Tempini (2015) further show that ICT and bureaucracy can be mutually reinforcing in public service delivery.

Digital-era governance represents an important transformation in the organization of public administration (Dunleavy et al., 2006), but it should not be interpreted as the complete disappearance of bureaucratic principles. Digital systems frequently require rules, classifications, access rights, authorization structures, audit trails, and standardized workflows. The technological medium changes, while many organizational principles remain.

Bannister and Connolly (2014) emphasize that digital transformation should also be evaluated in relation to public values. Efficiency and technological capability are not sufficient by themselves. Accountability, transparency, fairness, privacy, responsibility, and institutional legitimacy remain central. This reinforces the argument that digital transformation should be analyzed through organizational relationships rather than technology alone.

2.5. Functionalist and Interpretive Perspectives

Burrell and Morgan's (1979) paradigmatic framework provides a useful basis for bringing functionalist and interpretive readings into dialogue. A functionalist perspective highlights organizational order, standardization, performance, control, coordination, and system functioning. An interpretive perspective focuses on the meanings actors attach to organizational practices and technological change.

These perspectives are treated here as complementary rather than mutually exclusive. Digital transformation has material and organizational properties, yet its consequences depend on how digital systems are interpreted and enacted by organizational actors. The functionalist lens helps identify how digitalization changes procedures and control, while the interpretive lens helps explain why the same digital arrangement may be experienced as simplification by one manager and as additional control by another.

2.6. Algorithmic Management as an Emerging Institutional Layer

Algorithmic management refers in this chapter to the use of data-driven decision processes, automation, digital monitoring, performance systems, and decision-support technologies in managerial and administrative activities. It represents an advanced layer of digital transformation because organizational decisions increasingly depend on data infrastructures and computational tools.

Omidvar et al. (2023) provide an important bridge between technological change and organizational continuity through the concept of dynamic inertia. Their analysis suggests that organizations may respond to environmental change while reproducing established assumptions through routines. In public organizations, a paper authorization process may become an electronic authorization process; a manual reporting routine may become an automated dashboard; and a hierarchical chain may be encoded into software permissions. Technological adaptation therefore does not guarantee organizational adaptation.

Algorithmic consistency should not automatically be equated with substantive merit. A system can apply a criterion consistently while the criterion itself is incomplete, outdated, or poorly aligned with organizational objectives. Digital managerial competence consequently includes the ability to evaluate data, understand system limitations, communicate with technical specialists, and exercise critical and ethical judgement.

2.7. Middle-Level Managers as Mediating Actors

Middle-level managers occupy a distinctive position in public organizations. They translate strategic decisions into operational practice, coordinate employees and procedures, interpret institutional rules, and communicate implementation problems upward. Their position makes them particularly important for understanding digital transformation.

Their role becomes more consequential when bureaucracy and merit are considered together. Managers decide how rules are applied, how responsibilities are distributed, how competence is recognized, and how digital tools are integrated into work. They therefore mediate between formal institutional arrangements and operational realities. This mediating role is a central component of the ÇAM framework.

2.8. The Theoretical Propositions of the Chapter

P1. Digitalization and bureaucracy are jointly structured in middle-level managers' accounts.

P2. Bureaucracy may facilitate or constrain digital processes depending on how rules are designed and enacted.

P3. Merit is connected with digital competence and emerging algorithmic management practices.

P4. Algorithmic management has potential implications for performance, transparency, and accountability.

P5. Institutional outcomes are related to managerial perceptions and subsequent assessments of digitalization.

P6. Legislation, digital competence, and managerial culture gain importance alongside technological change.

P7. Middle-level managers mediate between strategic decisions and operational practice.

These propositions are analytical rather than deterministic. They organize the empirical assessment in Table 3 and guide the interpretation of the framework developed in Section 6.

3. Research Methodology

3.1. Research Approach and Design

The study employs a qualitative case study design. This design is appropriate because the research examines how public managers interpret and experience digitalization within the organizational context of public administration, with particular attention to the integrated relationship between bureaucracy and merit. The approach is interpretive in that organizational realities are examined through the meanings participants attach to their experiences. At the same time, functionalist dimensions such as standardization, control, performance, and organizational order are considered because they are visible in managerial accounts.

3.1.1. Research Questions

For the purposes of this chapter, the seven sub-questions developed in the doctoral thesis were consolidated into five integrated research questions in order to preserve their substantive scope while providing a more concise structure for the chapter.

The study is guided by the following questions:

RQ1: How do middle-level managers perceive digitalization and the role of Management Information Systems in public administration?

RQ2: How are middle-level managers' perceptions of bureaucracy shaped during digitalization processes?

RQ3: How do middle-level managers' perceptions of merit emerge in relation to digitalization and the use of information systems?

RQ4: How do middle-level managers evaluate artificial intelligence and algorithmic management in relation to managerial decision-making, performance, and merit?

RQ5: How are bureaucracy and merit jointly interpreted in relation to organizational outcomes and digital transformation?

3.2. Research Context and Participants

The empirical context consists of Turkish public organizations. The study group comprises 12 middle-level managers, including managers with department-head-level and comparable managerial responsibilities. Participants were selected through purposive sampling in accordance with the research purpose and research questions. This sampling strategy was used to obtain information-rich accounts from managers with relevant experience of organizational processes and digitalization.

3.3. Ethical Considerations and Confidentiality

The privacy and confidentiality of participants were protected by representing all participants through anonymized case codes (K1…K12). Participants' views are presented without including any personal or

directly identifying information, and, where necessary, findings are reported in aggregated form or paraphrased while preserving their substantive meaning in accordance with the confidentiality principles of the study. As the available research records do not specify an identifiable formal ethics committee approval number, no unverified ethics approval number is reported in this chapter.

3.4. Data Collection

Data were collected through semi-structured interviews. This technique provided a common thematic structure across interviews while allowing participants to explain experiences and interpretations in their own terms. The approach was appropriate because the study was concerned not only with what digital systems do but also with how managers understand their organizational consequences.

3.5. Data Analysis

Interview data were systematically coded and analyzed using MAXQDA. The analysis generated three principal thematic domains—digitalization, merit, and bureaucracy—with a total of 430 coding instances: 150 related to digitalization, 143 to merit, and 137 to bureaucracy. These frequencies describe the distribution of coding within the dataset and are not treated as measures of causal importance.

Table 1. Distribution of coding instances across the three principal themes

Principal theme	Coding instances
Digitalization	150
Merit	143
Bureaucracy	137
Total	430

Note: Author's analysis based on the interview dataset.

3.6. Bureaucracy-Merit as the Central Analytical Unit

The analytical procedure did not assume that bureaucracy and merit represented separate empirical worlds. Instead, their overlap was treated as substantively meaningful. A statement about rules could simultaneously concern competence, responsibility, performance, or suitability; likewise, a statement about managerial competence could concern the rules and organizational procedures through which that competence was exercised. This integrated treatment is central to the chapter's analytical contribution.

3.7. Analysis of Code Relationships

The results reported in the thesis indicate positive relationships between digitalization and merit ($r = .695$, $p = .0061$, $N = 12$), digitalization and bureaucracy ($r = .642$, $p = .0122$, $N = 12$), and bureaucracy and merit ($r = .991$, $p < .001$, $N = 12$). The exceptionally strong bureaucracy-merit relationship is analytically important because it is consistent with the qualitative interpretation that these dimensions were frequently constructed together in participants' accounts.

As a complementary analysis, Pearson correlations were examined using case-level coding measures for the three principal themes. For each of the 12 cases, the coding count assigned to digitalization, merit, and bureaucracy was used as the corresponding case-level measure. Pearson's product-moment correlation was selected because the purpose of this supplementary analysis was to describe linear associations among these case-level measures, rather than to test a causal model. The coefficients therefore function as descriptive relational indicators that complement the qualitative thematic analysis. No normalization or transformation of the case-

level coding counts is reported in the underlying analysis used for this chapter. The reported p-values and coefficients are reproduced from the underlying thesis analysis and are not recalculated in this chapter. Accordingly, the chapter does not use these statistics to claim statistical generalizability or causality.

Table 2. Pearson correlation indicators based on case-level coding measures

Code pair	r	p	Interpretation
Digitalization-Merit	.695	.0061	Positive association
Digitalization-Bureaucracy	.642	.0122	Positive association
Bureaucracy-Merit	.991	< .001	Very strong association

Note: Author's analysis based on case-level coding measures derived from the interview dataset. N = 12

3.8. Methodological Boundaries

The coefficients reported above are not interpreted as causal effects. They are Pearson correlation coefficients calculated from the case-level coding measures reported in the thesis and are used here as complementary evidence of relational patterning. They do not establish that digitalization causes changes in bureaucracy or merit. The qualitative design also does not support statistical generalization to all public organizations. Its value lies in identifying patterns of meaning, organizational relationships, and theoretically relevant mechanisms.

4. Empirical Findings

4.1. Overview of Findings

Across the 12 cases, digitalization was discussed together with questions of bureaucratic procedure, competence, managerial responsibility, performance, and institutional capacity. The distribution of the three principal coding domains-150 digitalization, 143 merit, and 137 bureaucracy-shows that all three themes received substantial analytical attention in the dataset; their interconnection is established through the

qualitative coding relationships and case-level analysis rather than through frequency proximity alone.

4.2. Digitalization as Organizational Reconfiguration

Managers' accounts indicate that digitalization changes procedures, information flows, responsibilities, monitoring arrangements, and decision-making conditions. Digital records can strengthen traceability; integrated systems can connect organizational units; automated workflows can redistribute tasks; and digital reporting can increase visibility. Yet these changes do not automatically alter the institutional logic underlying the process.

4.3. Bureaucracy-Merit as an Integrated Dimension

Participant K1 defines merit in strongly practice-oriented terms: "Merit is the person who performs the job best and knows the job best." (translated from Turkish).

Participant K10 similarly links competent personnel and effective bureaucracy: "Meritorious staff ensure that the process is managed properly, while effective bureaucracy guarantees the sustainability of the process." (translated from Turkish).

These excerpts are illustrative rather than exhaustive; the broader interpretation is based on the cross-case analysis of K1…K12.

The findings show that managers do not experience bureaucracy and merit as independent organizational dimensions. Bureaucracy is associated with rules, hierarchy, control, legal security, standardization, continuity, and predictability, but also with procedural burden, delay, excessive paperwork, and slower decision-making under certain conditions. Merit is understood in multidimensional terms, including competence, experience, performance, responsibility, managerial capability, professional knowledge, ethical judgement, and role suitability.

This duality is important. The data do not support an interpretation in which bureaucracy is inherently negative and merit inherently positive. Instead, the organizational value of rules and competence depends on how they are enacted together. Rules can protect merit by creating transparent procedures, while rigid procedures can prevent competent managers from responding effectively to context.

4.4. Digitalization and the Bureaucracy-Merit Relationship

Digitalization does not eliminate bureaucracy. Instead, bureaucratic elements are reconfigured through digital systems. Rules can become workflow requirements, paper records become electronic records, physical approvals become digital authorizations, and manual monitoring can become dashboard-based control. At the same time, digitalization changes the conditions under which competence is exercised and recognized.

The strongest complementary relationship in the analysis is between merit and bureaucracy ($r = .991$, $p < .001$, $N = 12$). This coefficient is not evidence of causality. Rather, it indicates a very strong association in the analyzed case-level coding measures. This result is consistent with the qualitative interpretation that managers frequently construct competence and merit through the organizational structures in which authority, responsibility, rules, and decisions operate.

4.5. Digital Competence and the Transformation of Merit

The findings indicate that participants understand merit as a multidimensional managerial capacity rather than merely as a formal qualification or appointment criterion. Expertise and experience remain important, but they are increasingly accompanied by digital competence, adaptability, problem-solving capacity, performance orientation, and ethical responsibility.

Digital competence should not be interpreted narrowly as technical skill. It includes the ability to interpret digital information, recognize limitations in data, understand system-generated recommendations, communicate with technical specialists, and make responsible decisions when digital outputs conflict with professional knowledge. In this sense, digital competence becomes a contemporary component of managerial merit.

4.6. Bureaucratic Processes as Both Constraint and Capacity

Managers' accounts reveal a dual perception of bureaucracy. Rules and formal procedures can provide legal security, accountability, order, and predictability. Conversely, unnecessary approval chains, repetitive documentation, and rigid procedures may create delay and reduce flexibility. Digitalization can intensify either dimension depending on whether existing procedures are redesigned or merely transferred into digital form.

4.7. Algorithmic Management and Human Judgement

Algorithmic management appears as an explanatory layer connected to digital competence, decision support, control, performance, and technological change. The findings do not justify treating algorithmic management as an independent causal variable. Instead, they indicate that data-driven systems can strengthen consistency, speed, monitoring, and traceability while creating new questions concerning transparency, accountability, data quality, human oversight, and professional discretion.

Managers who operate or supervise data-driven systems therefore require not only technical familiarity but also the capacity to understand the limits of automated outputs, recognize contextual differences, and maintain responsibility for administrative decisions. Algorithmic

management consequently strengthens rather than eliminates the need for qualified human judgement.

4.8. Institutional Outcomes and Feedback

Institutional outcomes such as efficiency, transparency, accountability, digital maturity, and citizen satisfaction should not be understood as automatic products of technology. They emerge through interaction among infrastructure, organizational rules, managerial practices, human capabilities, and institutional context. Outcomes can also influence subsequent managerial evaluations of digitalization and future organizational practices.

4.9. Legislation, Organizational Culture, and Institutional Capacity

The findings indicate that technological change alone is insufficient to explain transformation outcomes. Legislation, digital competence, managerial culture, organizational capacity, and institutional assumptions remain important. This supports an understanding of digital transformation as a socio-organizational process in which technology interacts with the institutional environment. This interpretation is also consistent with the OECD's review of Türkiye, which emphasizes institutional capacity, digital skills, governance, and data capabilities alongside technological development (OECD, 2023).

4.10. Middle-Level Managers as Mediating Actors

Middle-level managers are positioned between strategic decisions and operational implementation. Their interpretations shape how formal policies are translated into everyday practice. They decide how rules are applied, how responsibilities are distributed, how competence is recognized, and how digital tools are integrated into work. Their position therefore makes managerial perception an important part of the implementation process.

4.11. Proposition-Based Assessment

Table 3. Proposition-based assessment of the empirical findings

Proposition	Statement	Assessment	Evidence
P1	Digitalization and bureaucracy are jointly structured in managerial accounts.	Supported	Qualitative evidence
P2	Bureaucracy may facilitate or constrain digital processes depending on how rules are designed and enacted.	Supported	Qualitative evidence
P3	Merit is connected with digital competence and emerging algorithmic management practices.	Partially supported	Qualitative evidence
P4	Algorithmic management has potential implications for performance, transparency, and accountability.	Partially supported	Qualitative evidence
P5	Institutional outcomes are related to managerial perceptions and subsequent assessments of digitalization.	Supported	Qualitative evidence
P6	Legislation, digital competence, and managerial culture gain importance alongside technological change.	Strongly supported	Qualitative evidence
P7	Middle-level managers mediate between strategic decisions and operational practice.	Supported	Qualitative evidence

Note: Author's qualitative analysis.

5. Discussion

5.1. Digitalization as Reconfiguration Rather Than Replacement

The first major implication is that digital transformation should not be understood as a transition from bureaucracy to a non-bureaucratic organization. Digital systems often strengthen traceability, standardization, access control, documentation, and procedural consistency. These are recognizably bureaucratic functions even when implemented electronically.

This finding is consistent with Bovens and Zouridis (2002) and Cordella and Tempini (2015). Rather than disappearing, bureaucracy can become embedded in software, databases, workflows, permissions, and algorithmic routines. Digital modernization therefore does not necessarily equal organizational modernization.

5.2. The Bureaucracy-Merit Relationship as an Organizational Nexus

The strongest case-level association between bureaucracy and merit is theoretically important because it supports their conceptualization as an integrated organizational relationship. A person's competence becomes organizationally meaningful through the position they occupy, the responsibilities they receive, the rules under which they work, and the discretion available to them.

This interpretation also explains why merit can be experienced differently across institutional settings. Where rules are transparent and roles are clearly defined, bureaucratic arrangements can provide an institutional basis for merit. Where procedures become excessively rigid or personnel practices do not effectively recognize competence, the same arrangements may constrain merit-based practice (Ingraham, 1995; Peters & Pierre, 2004).

5.3. Dynamic Inertia and Organizational Continuity

Omidvar et al. (2023) provide a particularly useful contemporary lens for interpreting the coexistence of technological change and organizational continuity. Their concept of dynamic inertia explains how organizations may respond to environmental changes while continuing to reproduce established assumptions through routines. This helps explain why replacing a paper process with a digital process may change speed and visibility without changing the underlying logic of the process.

The distinction between technological adaptation and organizational adaptation is consequently central. An organization may become more technologically sophisticated while remaining institutionally similar. This is especially relevant when digital systems encode existing approval sequences, categories, authority structures, or performance assumptions.

5.4. Digital Competence as Contemporary Merit

The findings support an expanded interpretation of managerial merit. Professional competence, experience, responsibility, and performance remain important, but digital competence becomes increasingly necessary as public work is mediated by information systems, data, automation, and algorithmic routines. Contemporary merit is therefore multidimensional: it combines professional knowledge, managerial capability, digital competence, and critical and ethical judgement.

This interpretation is compatible with Simon's (1947) bounded rationality perspective. Digital systems can improve the information environment without eliminating cognitive and organizational limitations. Indeed, by structuring what is visible and actionable, systems may create new forms of bounded rationality. Competent managers remain necessary even when decision support becomes increasingly sophisticated.

5.5. Managerial Discretion Between Rules and Digital Systems

Digital systems can strengthen administrative accountability by making decisions more traceable and procedures more standardized. Yet excessive standardization may constrain contextual judgement. The central issue is therefore not whether discretion should disappear, but where discretion should be located and how it should be made accountable.

Middle-level managers occupy a critical position in this relationship. They translate formal rules into operational decisions and interpret system outputs in specific organizational contexts. Their role can therefore be understood as an interface between bureaucratic rationality and digital rationality. This interface is also where merit becomes visible through actual performance and responsibility.

5.6. Functionalist and Interpretive Integration

The combined functionalist and interpretive approach provides a more complete account than either perspective alone. A functionalist analysis highlights standardization, control, performance, and organizational order. An interpretive analysis reveals how managers assign meaning to these changes and how institutional experience shapes their responses.

This combined perspective is particularly useful because digital transformation is neither technologically deterministic nor entirely subjective. Digital systems have material and organizational properties, but their consequences depend on how they are designed, embedded, interpreted, and enacted. The empirical findings therefore support a relational and interpretive account of transformation.

6. The ÇAM Digital Bureaucracy-Merit Analytical Framework

6.1. Purpose and Position of the Framework

The label "ÇAM" refers to the author's surname and is used as the identifying name of the analytical framework developed in this chapter. It is not an acronym. The label is retained to distinguish this framework from other digital-government and bureaucracy frameworks and to identify the specific analytical structure developed from the present study.

The ÇAM Digital Bureaucracy-Merit Analytical Framework is developed from the intersection of the literature on digitalization, bureaucracy, merit, bounded rationality, algorithmic management, and the

empirical findings of the qualitative study. Its purpose is not to establish a deterministic causal model or a statistically validated path model. It is an analytical guide for examining how technological, organizational, managerial, and institutional dimensions are experienced and connected in public organizations.

6.2. The Five Analytical Layers

Layer 1: Digitalization Infrastructure

Artificial intelligence, big data, e-government, cloud systems, integrated information systems, automation, analytics, and decision-support technologies constitute the technological infrastructure of transformation.

Layer 2: Integrated Bureaucracy-Merit Dimension

This layer brings rules, hierarchy, authority, control, accountability, flexibility, expertise, experience, digital competence, performance, ethics, and role suitability into one analytical dimension. Bureaucracy and merit are not treated as separate axes.

Layer 3: Algorithmic Management

Data-driven decision processes, digital monitoring, automation, performance systems, and decision-support tools represent an advanced explanatory layer through which organizational routines may be reinforced or reconfigured.

Layer 4: Institutional Outcomes

Efficiency, transparency, accountability, digital maturity, service quality, and citizen satisfaction are considered outcomes through which the organizational consequences of digital transformation can be interpreted.

Layer 5: Environmental and Institutional Conditions

Public digitalization policies, legislation, technological development, organizational culture, institutional capacity, and prevailing assumptions surround and condition the other layers.

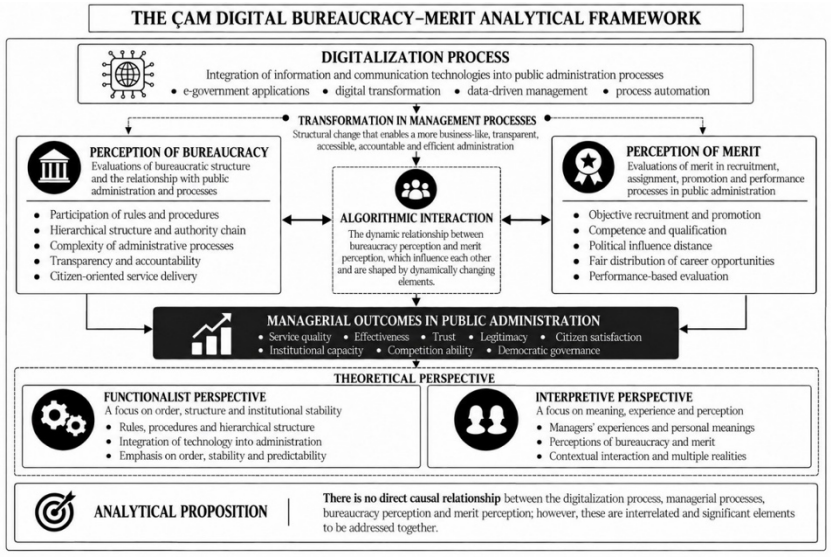


Figure 1. The ÇAM Digital Bureaucracy-Merit Analytical Framework

Note: The framework was developed by the author as part of ongoing doctoral research. The figure presents an analytical ordering device; it does not represent a deterministic causal pathway.

6.3. Analytical Flow

Digitalization Infrastructure → Bureaucracy-Merit Interaction → Algorithmic Management → Institutional Outcomes → Feedback

This sequence is an analytical ordering device rather than a statistical causal pathway. The empirical research supports the analysis of interaction, relational patterning, interpretation, and meaning-making among the elements. It does not establish that one element mechanically produces another.

6.4. Feedback and Cyclical Transformation

Institutional outcomes do not simply conclude the transformation process. Successful digital processes may strengthen confidence in digitalization and encourage further adoption, while unsuccessful processes may reinforce perceptions of bureaucratic rigidity, insufficient competence, or organizational resistance. The framework is therefore cyclical and feedback-oriented rather than strictly linear.

6.5. Middle-Level Managers within the Framework

Middle-level managers occupy a mediating position across the framework. They interpret digital systems, apply rules, allocate responsibilities, evaluate competence, and translate strategic decisions into operational practice. Their role connects technological infrastructure with the integrated bureaucracy–merit dimension and with institutional outcomes.

6.6. Theoretical Contribution of the Framework

The distinctive contribution of the ÇAM framework is its treatment of digitalization as an institutional reconfiguration of the bureaucracy-merit relationship rather than as a technological replacement of bureaucracy. This contribution is developed through seven related propositions.

First, the framework rejects a simple opposition between digitalization and bureaucracy. Digitalization can reduce unnecessary procedural burdens while simultaneously creating new digital forms of recording, monitoring, standardization, authorization, and control.

Second, the framework reinterprets merit in the digital context. Competence, experience, performance, professional knowledge, responsibility, and ethical judgement remain central, while digital competence becomes an increasingly relevant component of managerial capacity.

Third, and most centrally, the framework treats bureaucracy and merit as a single integrated analytical dimension. The exceptionally strong association in the case-level coding measures is consistent with their joint interpretation in participants' accounts. This is not presented as causal evidence; rather, it supports examining the two dimensions together instead of treating them as independent analytical axes.

Fourth, the framework positions algorithmic management as an explanatory layer within digital transformation rather than as an independent causal variable. Its consequences depend on the interaction of technology, rules, human competence, discretion, and accountability.

Fifth, the framework introduces a feedback-oriented structure in which institutional outcomes can influence subsequent managerial evaluations and future digitalization practices. Digital transformation is therefore understood as cyclical and adaptive rather than as a one-way technological progression.

Sixth, the framework recognizes that legislation, digital competence, and managerial culture condition how technological change is interpreted and enacted within public organizations.

Seventh, the framework explicitly positions middle-level managers as mediating actors between strategic policy and operational practice. Their interpretations and decisions connect technological infrastructure with the integrated bureaucracy-merit dimension and with institutional outcomes.

7. Implications

Taken together, these contributions distinguish the ÇAM framework from approaches that isolate digital technology, bureaucracy, or merit. Its value is not to provide a universal causal model, but to offer a parsimonious analytical structure for examining how these dimensions become connected in the lived and interpreted practice of public organizations.

7.1. Theoretical Implications

The chapter contributes to digital public administration research by conceptualizing bureaucracy and merit as an integrated organizational dimension. It also reframes digital transformation as institutional reconfiguration rather than the replacement of bureaucracy. The use of dynamic inertia provides a contemporary explanation for why technological adaptation can coexist with organizational continuity.

Finally, the chapter extends the concept of managerial merit by incorporating digital and critical capabilities into professional and managerial competence.

7.2. Managerial Implications

Digital transformation should not be treated as an information technology project alone. Public managers need continuous digital competence development, including data interpretation, system evaluation, responsible use of automation, and ethical judgement. Managers should also have sufficient decision responsibility to question digital routines when those routines reproduce outdated assumptions or create unintended organizational consequences. This is consistent with OECD guidance emphasizing the development of digital talent and skills as a core condition of successful digital government (OECD, 2021; Burtscher et al., 2024).

7.3. Policy Implications

First, public organizations should strengthen continuous digital competence development for managers and employees.

Second, merit-based personnel practices should recognize competence, relevant experience, role suitability, performance, professional responsibility, and digital competence rather than relying on formal qualifications alone.

Third, bureaucratic simplification should preserve rules that ensure legality, legal security, and accountability while redesigning unnecessary approval chains, repetitive documentation, and avoidable transaction burdens.

Fourth, digital and algorithmic systems used in administrative decision-making should incorporate transparency, accountability, human oversight, review mechanisms, and clear responsibility for decisions.

Fifth, organizations should distinguish between digitizing an existing procedure and redesigning the procedure itself. Before automating

a bureaucratic routine, they should examine whether the underlying rule remains necessary and whether the distribution of responsibility remains appropriate.

8. Conclusion

This chapter examined digital transformation through the relationship between bureaucracy and merit in public organizations. The qualitative findings indicate that digitalization does not eliminate bureaucracy. Instead, it reconfigures rules, hierarchy, control, documentation, and administrative processes through digital systems. Bureaucracy is experienced both as a source of order, legal security, standardization, and continuity and as a potential source of procedural burden and delay.

Merit is likewise interpreted broadly. Managers associate merit with competence, experience, performance, responsibility, managerial capability, professional knowledge, ethical judgement, and organizational role suitability. Digital transformation adds a further requirement: the capacity to work effectively and critically with digital systems. Merit in digital public administration therefore becomes increasingly connected to digital competence without being reducible to it.

The very strong bureaucracy–merit association supports the conceptualization of an integrated bureaucracy-merit analytical dimension. The positive relationships between digitalization and the other dimensions likewise indicate that these concepts are frequently constructed together in managerial accounts. These correlations are not causal estimates; they complement the qualitative interpretation by indicating relational patterns in the case-level coding measures.

The ÇAM Digital Bureaucracy-Merit Analytical Framework brings these findings together in a five-layer analytical structure comprising digitalization infrastructure; the integrated bureaucracy-merit dimension; algorithmic management; institutional outcomes; and environmental and institutional conditions. The framework emphasizes interaction and feedback rather than a deterministic sequence.

The central conclusion is that digital transformation should be understood through both technology and organizational meaning. Public organizations do not simply become digital; they reorganize the ways in which rules, responsibilities, competence, discretion, and accountability are enacted. The future of digital public administration therefore depends not on eliminating bureaucracy, but on developing an adaptive relationship among digital technologies, bureaucratic structures, managerial competence, and merit-based practice.

8.1. Limitations and Directions for Future Research

The study is based on 12 middle-level managers and a qualitative case study design. Its findings should therefore not be statistically generalized to all public organizations. The case-level coding relationship analysis is complementary and does not establish causal relationships. Future research could examine the ÇAM framework through larger quantitative samples, comparative studies across organizational types and administrative traditions, longitudinal designs, and direct investigation of artificial intelligence and algorithmic management in public administration. Further research could also examine whether digital competence becomes an institutionalized component of merit or remains an informal expectation.

Declarations

Ethics Committee Approval: This chapter is derived from the author's doctoral thesis. Ethical requirements related to the original research were addressed within the scope of the doctoral study.

Use of Artificial Intelligence: In this chapter, AI-assisted language editing was used solely to improve grammar, clarity, readability, and academic English. The author retains full responsibility for the research design, empirical analysis, interpretation of findings, and substantive content of the chapter.

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Chapter 9:

Programmatic Advertising as a Data-Driven Information System: Personalization, Automation, and Managerial Challenges

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Abstract

Advances in digital technologies have significantly transformed the ways in which advertising activities are planned, purchased, targeted, and evaluated. Programmatic advertising, one of the prominent applications of this transformation, is a system based on the real-time buying and selling of advertising inventory through data, algorithms, and automation technologies. The development of programmatic advertising extends beyond the automation of advertising purchasing processes, giving rise to a multidimensional structure that involves the processing of user data, identification of target audiences, personalization of advertising content, and algorithmic decision-making. This chapter aims to provide a comprehensive examination of the conceptual and technological structure of programmatic advertising and to evaluate it from a Management Information Systems perspective. To this end, the chapter first examines the transformation of digital advertising toward programmatic advertising, followed by an analysis of its core components, personalization and targeting strategies, benefits, and associated risks. Finally, programmatic advertising is evaluated within the MIS context through the dimensions of data management, decision support systems, algorithmic decision-making, data quality, transparency, accountability, and information security. The discussion presented in this chapter suggests that programmatic advertising should be understood not merely as a digital marketing or advertising purchasing method, but as a sociotechnical information system shaped by the interaction between technological and managerial elements.

Keywords: programmatic advertising, digital advertising, personalization, algorithmic targeting, management information systems, data-driven decision-making

1. Introduction

Digitalization has evolved beyond merely changing the communication channels used in the advertising industry and has become a structural transformation that reshapes how advertisements are produced, purchased, targeted, and evaluated. While traditional advertising purchasing processes have largely relied on human intervention, predetermined media plans, and fixed advertising placements, digital environments have brought automation, real-time data processing, and algorithmic decision-making to the forefront of advertising activities. Within this transformation, programmatic advertising has created a new advertising ecosystem based on the real-time buying and selling of advertising inventory through technology and data (Busch, 2016; Uday Kiran & Arumugam, 2020). The rise of programmatic advertising can therefore be regarded not merely as a technical change in advertising purchasing methods, but as a broader transformation of advertising activities into a data-driven decision-making system.

One of the distinguishing characteristics of programmatic advertising is that the relationship among advertisers, publishers, and users is mediated through technological platforms and algorithms. Interconnected structures such as demand-side platforms, supply-side platforms, data management platforms, and ad exchanges enable decisions concerning advertising impressions to be made automatically within extremely short periods of time. Real-time bidding mechanisms allow each advertising impression to be evaluated according to user and contextual characteristics and priced through an auction-based process (Yuan et al., 2013; Wang et al., 2017). Advertising is thus evolving from a traditional structure based on the bulk purchasing of predetermined media space toward a data-intensive system in which decisions can be made at the level of individual users and individual impressions.

A major consequence of this transformation is that personalization has become a core function of programmatic advertising. Data derived from users' demographic characteristics, locations, browsing histories, click behaviors, and previous interactions enable advertisements to be

tailored to specific users or user groups (Boerman et al., 2017; Tran et al., 2020). With advances in artificial intelligence and machine learning technologies, this structure is increasingly moving toward more sophisticated predictive and contextual personalization practices. However, alongside the effectiveness and efficiency benefits offered by programmatic advertising, data-intensive personalization also raises significant concerns regarding user privacy, perceived intrusiveness, algorithmic opacity, and accountability (Palos-Sánchez et al., 2019; Samuel et al., 2021).

This dual nature of programmatic advertising makes it insufficient to examine the phenomenon solely from a marketing or advertising perspective. On the one hand, the system provides advertisers with a data-driven optimization mechanism that enables them to reach the right user at the right time. On the other hand, it requires the collection, classification, processing, and use of large volumes of user data in algorithmic decision-making processes. Moreover, the system requires the integration of different technological platforms, the maintenance of data reliability and security, and the effective management of algorithmic decisions. These characteristics make programmatic advertising an important area of inquiry from a Management Information Systems perspective.

MIS is regarded as an interdisciplinary field that integrates information technologies, data, and management processes in ways that support organizational activities and decision-making mechanisms (Damar & Coşkun, 2017). From this perspective, programmatic advertising can be viewed as a contemporary application of several core MIS domains, including data management, systems integration, and decision support mechanisms, within the context of digital advertising. Programmatic advertising algorithms process numerous data points in real time to automate decisions related to advertising allocation, targeting, and pricing. Consequently, the effectiveness of the system depends not only on the performance of the algorithms employed but also on the integrated management of technological and managerial factors such as data quality, system security, transparency, auditability, and governance.

Accordingly, this chapter examines programmatic advertising from a Management Information Systems perspective. It first traces the transformation of digital advertising and outlines the programmatic ecosystem, then discusses personalization and targeting strategies together with the benefits and risks of the system, and finally evaluates programmatic advertising in terms of data-driven decision-making, algorithmic control, data governance, transparency, and information security.

2. Literature Review

2.1. Evolution and Transformation of Digital Advertising

With technological advancements, the use of automation and artificial intelligence-supported applications in digital advertising has become increasingly widespread, while programmatic advertising has emerged as an alternative approach to traditional advertising purchasing processes (Deng et al., 2019). Whereas traditional advertising relies on manual negotiations and fixed placements, PA differs by employing automation, real-time data analytics, and dynamic optimization (Neves & Pereira, 2025). PA is fundamentally transforming both the decision-making processes and implementation practices of advertising activities (Dwivedi et al., 2021). As interest in digital channels has increased, businesses have become increasingly reliant on digital advertising (Ciuchita et al., 2023).

One of the key indicators demonstrating the economic dimension of this transformation is the growth recorded in programmatic advertising. It should be noted at the outset that the figures reported in this field are not directly comparable across sources, because the two sources cited below measure different quantities: Statista reports *programmatic advertising expenditure*, that is, the volume of advertising spending channelled through programmatic channels, whereas Grand View Research reports *programmatic advertising market size*, a broader measure based on a different

definition, reference period, and forecasting methodology. According to Statista's 2026 update, global programmatic advertising expenditure reached an estimated USD 595 billion in 2024 and is expected to approach USD 800 billion by 2028 (Guttmann, 2026). According to Grand View Research (2024), the global programmatic advertising market reached USD 678.4 billion in 2023 and is projected to grow at a compound annual growth rate of approximately 22.2% between 2024 and 2030, reaching USD 2,753.0 billion by 2030. Because these two series rest on different scopes, reference periods, and forecasting horizons, they should not be read as successive observations of a single trend; the difference between them reflects definitional and methodological differences between the two sources rather than a change in the market itself. The growing importance of programmatic advertising alongside the increasing adoption of automation, data utilization, and algorithmic targeting practices in digital advertising further illustrates this trend (Deng et al., 2019; Ciuchita et al., 2023). By integrating automation with data-driven decision-making mechanisms in digital advertising purchasing processes, PA enables advertisers to manage their targeting and purchasing activities more effectively (Busch, 2016; Uday Kiran & Arumugam, 2020).

An examination of the historical development of programmatic advertising indicates that internet advertising dates back to the 1990s, while the foundations of PA were established in the early 2000s (Gonzalvez-Cabañas & Mochón, 2016). During its early stages, manual negotiations between advertisers and publishers dominated digital advertising purchasing. With the development of Google AdWords, personalized advertisements based on users' search terms began to be delivered, contributing to the widespread adoption of targeted advertising practices (O'Shea, 2019). Following the expansion of advertising networks, ad exchanges emerged in which advertising inventory could be bought and sold through real-time bidding mechanisms (Gonzalvez-Cabañas & Mochón, 2016). This transformation is described by Busch (2016) as the beginning of a new era in which advertising purchasing transactions that had previously been performed manually were replaced by systems capable of automating millions of decisions using real-time

data. From the 2010s onward, PA continued to evolve through centralized media buying platforms, progressing from retargeting practices toward consumer-centric, data-driven advertising strategies (Turow, 2023).

Table 1 summarizes the major milestones in the transition from digital advertising to programmatic advertising.

Table 1. Transformation from digital advertising to programmatic advertising

Period	Characteristics	Core Technologies
1990s	Emergence of the first digital advertisements and predominantly manual advertising purchasing processes (Turow, 2023).	Banner advertisements and web-based advertising spaces
2000s	Rise of advertising networks, development of targeted advertising, and increasing use of user data in advertising processes (Turow, 2023).	Google AdWords (rebranded as Google Ads), cookies, and advertising networks
2010s	Emergence of real-time bidding, automated advertising purchasing, and widespread adoption of PA (Gonzalvez-Cabañas & Mochón, 2016; Busch, 2016).	Demand-side platforms, supply-side platforms, data management platforms, ad exchanges, and RTB
2020s and beyond	Development of data-driven automation, algorithmic optimization, and AI- and ML-supported targeting and personalization (Turow, 2023).	AI, ML, big data, and algorithmic targeting

2.2. Definition and Components of Programmatic Advertising

Programmatic advertising is defined as the automated process of buying and selling advertising inventory in real time through the use of technology and data (Uday Kiran & Arumugam, 2020). This definition clearly reflects the automation and data-driven decision-making mechanisms that constitute the fundamental operating logic of the system. PA enables advertising auctions to be conducted in real time through automation mechanisms supported by artificial intelligence and machine learning (Busch, 2016). Similarly, PA is regarded as a dynamic process that optimizes information flows through systems that manage user data,

thereby enhancing the profitability of digital marketing strategies (Palos-Sánchez et al., 2019).

One of the most critical components of PA is real-time bidding, which is based on the instantaneous evaluation of each advertising impression and its pricing through an auction mechanism (Yuan et al., 2013). Through real-time data exchange, PA provides a more cost-efficient and scalable advertising system connecting buyers, sellers, and intermediaries (Alaimo & Kallinikos, 2018). Within this mechanism, when a user requests a web page, available advertising spaces are filled with content from the advertiser submitting the highest bid (Häglund & Björklund, 2024). The PA ecosystem consists of various interconnected platforms that operate in an integrated manner to manage data-driven advertising processes. Table 2 presents a comparative overview of the primary functions of these platforms.

Table 2. Platforms in the programmatic advertising ecosystem

Platform Type	Primary Function	Users	Example Task
Demand-Side Platform	Enables advertisers to automatically access and purchase digital advertising inventory across different publishers (Busch, 2014; Wang et al., 2017).	Advertisers and media agencies	Conducting real-time bidding based on user and contextual data and optimizing advertising impressions
Supply-Side Platform	Enables publishers to offer their advertising inventory for sale through programmatic channels and optimize advertising revenues (Busch, 2014; Cooper et al., 2023).	Publishers	Offering advertising inventory for auction and evaluating bids submitted by eligible buyers
Data Management Platform	Collects and organizes user data obtained from different sources for segmentation and audience creation (Alaimo & Kallinikos, 2018; Miralles-Pechuán et al., 2023).	Advertisers, agencies, and DSPs	Categorizing user data to create audience segments and support targeting processes

Demand-side platforms are systems that enable advertisers to purchase advertising inventory in order to reach their target audiences

(Wang et al., 2017). Supply-side platforms, in contrast, are systems that enable publishers to automatically offer their digital advertising inventory for sale (Busch, 2016). Data management platforms play an important role in the advertising ecosystem by collecting user data from different sources, integrating and segmenting these data, and supporting advertising targeting processes (Chen et al., 2019; Núñez-Barriopedro et al., 2023). Together, these three types of platforms form an integrated structure, transforming the delivery of an advertising impression into an automated process that takes place within milliseconds (Uday Kiran & Arumugam, 2020).

2.3. Personalization in Programmatic Advertising

Personalized advertising involves delivering customized promotional messages to consumers based on their internet browsing histories and online behaviors (Tran et al., 2020). Aguirre et al. (2016) note that marketers frequently employ personalization strategies in online communications. Graf et al. (2025) emphasize that, as an alternative to personalized advertising based on behavioral tracking data, contextual advertising can enable effective ad placement without requiring user tracking. Table 3 provides a comparative overview of these strategies.

Table 3. Comparison of personalization and targeting strategies

Strategy	Definition	Type of Data Used
Demographic Targeting	Identification of target audiences based on demographic characteristics such as age, gender, income, and education level (Shaddy et al., 2026).	Demographic data
Location-Based Targeting	Tailoring advertisements according to the consumer's physical or geographic location (Thapa et al., 2024).	Location and GPS data
Behavioral Targeting	Tracking users' online behaviors and delivering individualized advertisements based on the behavioral data obtained (Boerman et al., 2017).	Browsing history, clicks, and online interaction data

Contextual Targeting	Matching advertisements with the semantic and contextual characteristics of the content being viewed rather than tracking user behavior (Häglund & Björklund, 2024; Graf et al., 2025).	Contextual and semantic data related to the content being viewed
Retargeting	Retargeting users who have previously interacted with a brand, product, or website (Bleier & Eisenbeiss, 2015).	Previous visit, interaction, and conversion data

In recent years, personalization practices in PA have evolved toward a new stage conceptualized as algorithmic hyper-personalization. Mohiuddin (2024) defines hyper-personalization as the extreme end of the personalization continuum and explains this approach through dimensions such as predictive accuracy, data breadth, temporal depth, contextual sensitivity, and cross-channel integration.

2.4. Advantages and Risks of Programmatic Advertising

The benefits that PA offers advertisers include cost advantages, efficiency, precise targeting, real-time optimization, and scalability (Busch, 2016; Dörnyei, 2021). However, PA also presents significant challenges. Samuel et al. (2021) conceptualize this complexity around three major areas of tension: personalization, mechanization, and effectiveness. As illustrated in Figure 1, the authors argue that these three areas of tension interact with one another, creating a level of complexity within the PA system that both complicates academic research and makes it more difficult for practitioners to critically evaluate the system.

The PA system is characterized by a tripartite stakeholder structure consisting of providers, adopters, and consumers, operating across technical, economic, and social dimensions. Moreover, each of these tensions encompasses antagonistic factors that are inherently embedded within the PA system (Samuel et al., 2021). PA relies on large-scale data collection mechanisms; however, such practices may be perceived as intrusive by users and may intensify privacy concerns (Palos-Sánchez et al., 2019).

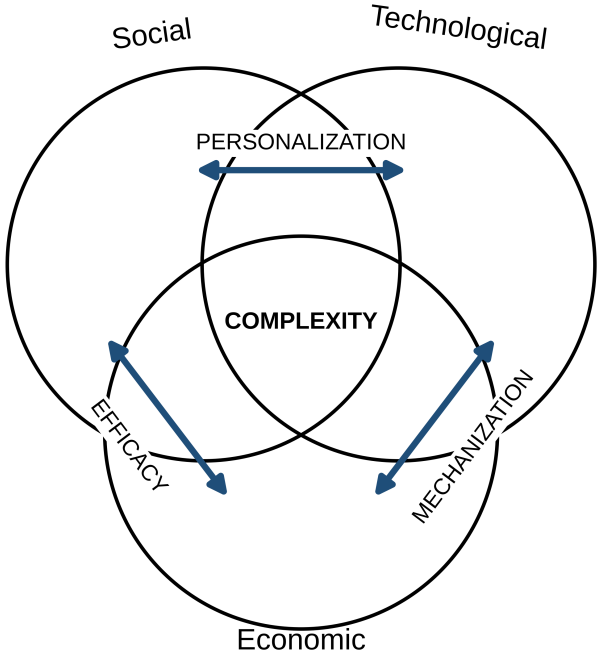


Figure 1. Systemic Complexity of Programmatic Advertising (adapted from Samuel et al., 2021)

Research indicates that approximately 57.4% of all purchased advertising inventory is not viewable, 14.5% is sold fraudulently, and 17.5% poses brand-safety risks (Gusic & Stallone, 2020; Dörnyei, 2021). Due to its high level of sociotechnical complexity, PA is frequently criticized for a lack of transparency and accountability, leading many advertisers to perceive the system as a "black box" (Dörnyei, 2021; Pärssinen et al., 2018). Jeon (2021) further draws attention to problems concerning the transparency of costs and fees across the intermediary chain in programmatic advertising.

2.5. Programmatic Advertising from a Management Information Systems Perspective

As outlined in the Introduction, MIS is not merely a management tool but also constitutes a technological infrastructure; it lies at the intersection of business and computing (Damar & Coşkun, 2017), and programmatic advertising represents one of the most contemporary

examples of this intersection. The relationship between PA and MIS has become an increasingly important area of interest in information systems research (Stange, 2017). Stange (2017) examines, within a Bayesian modeling framework, how decision support systems can optimize multichannel advertising effectiveness through user behavior modeling in real-time advertising. This study provides an important theoretical foundation for understanding how PA algorithms function as decision support systems. From an MIS perspective, PA is therefore not merely a marketing activity but also a complex information system and a data-driven decision-making mechanism. PA is built upon a big data-driven infrastructure and automates real-time digital advertising transactions through algorithms (Palos-Sánchez et al., 2019).

Shapiro and Varian (1999) emphasize that information has become a strategic resource for businesses in the information economy. In this context, programmatic advertising can be regarded as a contemporary application of the data-driven decision support functions of MIS within digital advertising. For organizations, MIS constitutes one of the most important components of decision-making by reducing the time and effort required and enabling decisions to be made more reliably, accurately, and efficiently. PA algorithms function as decision support systems by processing consumer data in real time and automating decisions concerning advertising allocation and pricing. Ananny and Crawford (2018) argue that the accountability of algorithmic systems is not merely a technical issue but also a matter of institutional governance. According to the authors, the auditability of algorithmic decision-making processes is essential for establishing trust in these systems. This highlights the need to incorporate transparency and accountability mechanisms into the design of PA systems. Within MIS, different types of information systems are required at different managerial levels to support sound and appropriate decision-making in addressing different types of problems. This structure is illustrated by the MIS Information Pyramid presented in Figure 2 (Tecim, n.d.).

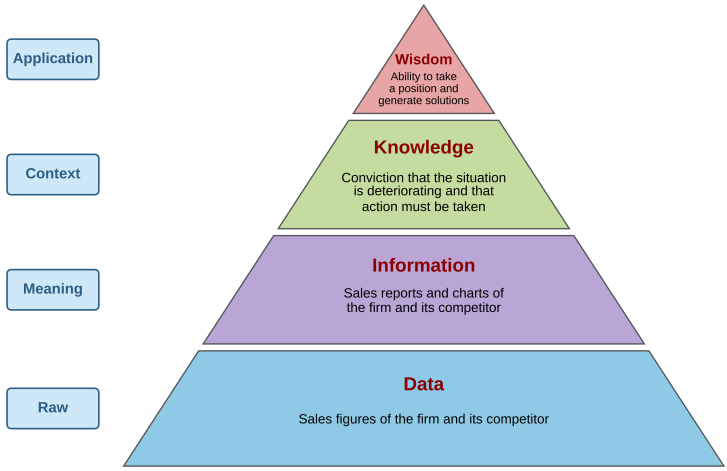


Figure 2. Management Information Systems Information Pyramid (adapted from Tecim, n.d.)

At the base of the MIS information pyramid lies data, followed upward by information and knowledge, while wisdom occupies the highest level of the pyramid (Özen, 2016; Tecim, n.d.). This pyramid conceptualizes data processing and the generation of meaningful information that also underpins PA systems. Contemporary MIS research emphasizes the need to reinterpret the information pyramid within the context of digital marketing. Key characteristics of MIS include the use of relational databases, timely and convenient managerial access to information, flexibility, system security, support for structured decision-making, and a focus on intra-organizational operations (Özen, 2016).

Bodó et al. (2017) characterize the problems encountered in PA as an "algorithmic control crisis," arguing that the lack of algorithmic transparency prevents individuals from exercising control over their digital actions. Similarly, Pasquale (2015), through the concept of the "black box society," provides a detailed analysis of the risks that the opacity of algorithmic decision-making systems creates for individuals and institutions. From an MIS perspective, designing PA systems within a more transparent, reliable, and ethical framework is therefore not merely

a technical requirement but also a strategic management imperative. When evaluated within the framework of MIS data management principles, these platforms play a key role in organizational management because they concern the confidentiality, integrity, and availability of data and information, which constitute some of the most valuable resources of organizations (Antunes et al., 2021).

Another important dimension in evaluating PA from an MIS perspective concerns data quality and governance standards (Redman, 2008). PA is regarded not only as a technological system but also as a sociotechnical structure and simultaneously functions as an interactive information technology system that shapes consumer behavior (Samuel et al., 2021). This transformation extends beyond the traditional boundaries of MIS by redefining both the operational structure of advertising and the nature of its interaction with users. In this context, the design and management of PA systems are closely related to core areas of the MIS discipline, including data security, systems integration, and decision theory.

3. Discussion

The development of programmatic advertising demonstrates that the transformation taking place in digital advertising cannot be explained solely by changes in technological tools. The transition from manual advertising purchasing processes to real-time and algorithmic decision-making mechanisms has also transformed the roles of actors within the advertising ecosystem and the ways in which decisions are made. Technological intermediaries such as DSPs, SSPs, DMPs, and ad exchanges have enabled many functions that were previously performed through interactions between individuals and organizations to be carried out through software systems (Busch, 2016; Wang et al., 2017). This indicates that, at its core, programmatic advertising represents a structure in which automation and data-driven decision-making converge.

One of the most prominent outcomes of this structure is personalization. By processing user and contextual data, programmatic systems enable advertisers to engage in more precise targeting. Applications ranging from demographic and location-based targeting to behavioral targeting, retargeting, and contextual targeting seek to achieve a closer match between advertising messages and users. However, increasing the level of personalization does not necessarily generate more favorable user responses in all circumstances. While personalized advertisements may enhance advertising effectiveness when users perceive them as relevant and useful, the scope of the data employed or the intensity of tracking practices may be perceived as intrusive (Bleier & Eisenbeiss, 2015; Boerman et al., 2017). Therefore, a tension exists between the technological capabilities offered by programmatic advertising and consumers' expectations of privacy, and this tension needs to be carefully managed.

This tension also demonstrates that the benefits and risks of programmatic advertising should not be evaluated independently of one another. Real-time optimization, precise targeting, scalability, and cost efficiency constitute major advantages for advertisers, whereas advertising fraud, brand safety, privacy, transparency, and accountability concerns represent risks arising from the same technological structure. The analysis by Samuel et al. (2021) makes this dual nature particularly visible by explaining programmatic advertising through systemic tensions centered on personalization, mechanization, and effectiveness. Consequently, evaluating the success of programmatic advertising solely on the basis of advertising performance indicators or technological efficiency is insufficient.

Algorithmic opacity, in particular, brings the managerial dimension of the system to the forefront. The involvement of numerous actors and algorithmic intermediaries in the delivery of advertising impressions within the programmatic advertising ecosystem may make it difficult to trace how decisions are made and how advertising expenditures are distributed. This has led to discussions of programmatic systems in terms of their "black box" characteristics (Pasquale, 2015; Pärssinen et al., 2018).

In light of Ananny and Crawford's (2018) discussion of algorithmic accountability, making the algorithm itself visible is not sufficient; the organizational, technological, and institutional structures surrounding the algorithm must also be taken into consideration.

At this point, an MIS perspective contributes to a more comprehensive understanding of programmatic advertising. From an MIS perspective, programmatic advertising can be conceptualized as an information and decision system in which user, contextual, and advertising data constitute the inputs; these data are processed through algorithms and integrated platforms; and the outputs take the form of decisions concerning ad delivery, pricing, and targeting. The transformation of raw data into information that can be used for decision-making also corresponds to the data–information–knowledge relationship within MIS. Accordingly, the performance of programmatic advertising is closely associated not only with the accuracy of algorithmic models but also with the quality and reliability of the data entering the system (Redman, 2008).

The sociotechnical nature of programmatic advertising is also particularly important. The system is shaped not only by technological infrastructure, algorithms, and data but also by the relationships among advertisers, publishers, technology providers, and consumers (Samuel et al., 2021). Therefore, the fact that a particular targeting or personalization practice is technically feasible does not automatically mean that it is managerially or ethically acceptable. Incorporating mechanisms for data security, user privacy, transparency, and accountability into system design is important for the long-term reliability of programmatic advertising.

Taken together, these considerations indicate that the central managerial question in programmatic advertising is not simply "How accurately can advertisements be targeted?" Equally important is the question: "With what data, through which decision-making mechanisms, and with what degree of transparency and accountability should targeting be conducted?" Such an approach makes it possible to conceptualize programmatic advertising as an MIS problem in which technological performance and governance requirements must be evaluated together.

4. Conclusion

Programmatic advertising represents one of the most significant outcomes of the transformation of digital advertising driven by automation, big data, and algorithmic decision-making. Unlike traditional advertising purchasing processes, programmatic advertising manages interactions among advertisers, publishers, and users through real-time data flows and interconnected technological platforms. The ecosystem formed by DSPs, SSPs, DMPs, ad exchanges, and RTB mechanisms enables advertising impressions to be evaluated, priced, and matched with specific users or user groups within extremely short periods of time.

The development of programmatic advertising has also expanded the scope of personalization practices. The ability to utilize different types of data, ranging from users' demographic characteristics and online behaviors to contextual information, enables advertisements to be delivered in a more relevant and targeted manner. However, the increasing capacity for personalization also raises concerns regarding privacy, perceived intrusiveness, and user control due to the extensive collection and processing of user data. Therefore, rather than pursuing the highest technologically achievable level of personalization, it is important to establish a balanced approach that considers both advertising effectiveness and users' rights and expectations.

Similarly, the speed, scalability, cost advantages, and real-time optimization capabilities offered by programmatic advertising cannot be considered independently of risks such as advertising fraud, brand safety, algorithmic opacity, and accountability. The multi-actor and technologically complex structure of the programmatic ecosystem can make it difficult to trace transactions within the system and understand the rationale underlying algorithmic decisions. This makes it necessary to consider transparency and governance mechanisms, alongside system performance, as fundamental elements in the sustainable development of programmatic advertising.

In this context, the Management Information Systems perspective provides an appropriate framework for evaluating the technological and managerial dimensions of programmatic advertising together. Programmatic advertising is directly related to the core domains of MIS because it involves the collection and processing of large volumes of data for decision-making purposes, the integration of different information systems, and the automation of decisions through algorithms. From this perspective, programmatic advertising should be regarded not merely as an advertising technology but as a sociotechnical decision system constituted by the interaction of data, algorithms, technological platforms, organizational actors, and users.

In conclusion, the future of programmatic advertising is unlikely to be determined solely by more sophisticated targeting algorithms or higher levels of automation. Data quality, information security, privacy, transparency, accountability, and governance mechanisms must evolve alongside technological developments. Holistic approaches developed from an MIS perspective can help organizations leverage the data-driven decision-making capabilities of programmatic advertising while managing the technical, managerial, and ethical risks associated with the system. In this way, programmatic advertising can move beyond being viewed merely as an automation technology for more efficient ad delivery and instead be understood within a reliable, manageable, and accountable digital information ecosystem.

Declarations

Ethics Committee Approval: This chapter is derived from the author's doctoral dissertation, conducted in the Management Information Systems PhD Program, Graduate Education Institute, İstanbul Topkapı University. Ethics committee approval for the dissertation research was obtained from the İstanbul Topkapı University Scientific Research and Publication Ethics Committee (decision no. 2025/16, dated 5 May 2025; document no. E-49896378-050.04-2500010797).

Use of Artificial Intelligence: In this chapter, artificial intelligence tools were used for language editing, proofreading, and assistance with citation formatting. AI tools were not used to generate scientific content, analyze data, or formulate the arguments presented in the chapter. All AI-assisted output was reviewed and verified by the author, who takes full responsibility for the content of the chapter.

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Third-Party Materials and Permissions: Figure 1 is adapted from Samuel et al. (2021), and Figure 2 is adapted from Tecim (n.d.) and translated into English. Both figures were redrawn by the author, and the original sources are cited in the figure captions. All tables were prepared by the author on the basis of the cited literature and contain no reproduced third-party material.

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Chapter 10:

The Evolution of Big Data Architectures: From Traditional Data Management to Data Lakehouses

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Abstract

The rapid growth in data volume, variety, and generation speed has led to a significant transformation in data management architectures. This study examines the evolution of Big Data architectures from traditional file-based systems and relational databases to Data Warehouses, Data Lakes, and Data Lakehouses. The main characteristics, data processing approaches, advantages, and limitations of these architectures are discussed comparatively. The study also examines cloud-based Big Data platforms, distributed data processing technologies such as Apache Spark and Apache Kafka, and the integration of Big Data with Business Intelligence and Artificial Intelligence applications. In addition, current challenges such as data quality, metadata management, data governance, and the risk of Data Lakes becoming Data Swamps are discussed. Finally, the study highlights the management of data structures required by Machine Learning applications and high-dimensional data as important research topics for the future development of Data Lake and Lakehouse architectures.

Keywords: big data, data lakehouse, data warehouse, data lake, data management

1. Introduction

The acceleration of digitalization processes, the diversification of data generation sources, and industrial transformations have created the need for a major change in approaches to data storage, processing, and analytical interpretation. In the early stages of information systems, traditional data management structures were based on file-based systems and Relational Database Management Systems (RDBMS). These systems stored data in structured forms under strict schemas and supported continuous daily operational processes (OLTP) with high consistency and Atomicity, Consistency, Isolation, Durability (ACID) guarantees. However, when organizations needed to integrate large volumes of data to support historical analysis and strategic decision-making, operational databases faced performance limitations when handling complex analytical queries (OLAP). This limitation led to the development of the Data Warehouse architecture, in which data is cleaned through ETL (Extract, Transform, Load) processes, collected in a centralized structure, and used to support Business Intelligence (BI) applications.

After the 2000s, especially with the widespread use of the Internet of Things (IoT), sensors, social media, and mobile systems, the era of "Big Data" began, being defined by the dimensions of Volume, Velocity, Variety, Veracity and Value (5Vs). Traditional Data Warehouses started to become insufficient because of their high costs, predefined schema requirements, and limitations in processing unstructured data. To overcome these structural limitations, Data Lakes emerged and enabled heterogeneous and raw data to be transferred at high speed to low-cost cloud object storage or distributed file systems (DFS) without any prior transformation, based on the schema-on-read principle. However, the lack of ACID transaction guarantees, schema management, and data governance in Data Lakes led over time to a decline in data quality, performance losses caused by the "small file problem," and the transformation of these systems into uncontrolled *"Data Swamps"*.

This methodological limitation in today's data ecosystem has led to the emergence of the Data Lakehouse architecture, which combines the ACID reliability, high SQL performance, and strong data governance of Data Warehouses with the flexible, scalable, and low-cost structure of Data Lakes. By using Open Table Formats such as Delta Lake, Apache Iceberg, and Apache Hudi, this new approach builds logical transaction logs on the object storage layer. Within the Medallion Architecture, it provides a gradual transition from raw data to processed data and supports both traditional Business Intelligence reporting and advanced analytics and machine learning processes on the same infrastructure. This study aims to examine the evolution of Big Data technologies, starting from traditional file-based and relational data management systems, as well as the technical characteristics and operational capabilities of Data Warehouse, Data Lake, and Data Lakehouse architectures and the transformation processes among these architectures from a comprehensive perspective.

2. Evolution of Big Data

2.1. Traditional Data Management

Data management includes all processes carried out to store, organize, access, and maintain the usability of data. In the early stages of information systems development, these processes were mainly performed through file-based systems. In the file-based approach, each application or user group stores the required data in its own files and performs operations on these files (Elmasri & Navathe, 2008). Although traditional file-based data management provides a practical approach, especially for storing and sharing limited amounts of data, various management problems arise as the amount of data and the number of users working with the data increase (Weidmann, 2023).

The relational data model, proposed by Codd in 1970, introduced an important transformation in data management by enabling data to be represented based on relationships. In the relational model, data is represented in tables consisting of rows and columns, and logical

relationships between data are established through common values. This approach contributed to reducing the dependency between the physical storage structure of data and the logical view of data presented to users (Codd, 1970).

With the widespread use of relational database management systems (RDBMS), functions such as data integrity, data security, concurrent access, and querying became centrally manageable. Relational databases structure data in tables consisting of rows and columns. The system maintains data integrity through primary key and foreign key relationships, while ACID properties support the reliable and consistent execution of transactions (Coronel & Morris, 2015; Silberschatz et al., 2020).

The limitations of traditional file-based data management approaches in handling large data volumes, concurrent data processing, and data integrity created the need to move toward Database Management Systems and modern Data Warehouse architectures.

Since relational databases are mainly used to support daily operational transactions, new requirements have emerged over time for analyzing large volumes of historical data and using them in decision-support processes (Kimball & Ross, 2002). RDBMS structures, which are designed to record daily transactions quickly, frequently, and securely, have shown significant performance limitations when handling long-term and complex analytical queries across an organization (Coronel & Morris, 2015; Elmasri & Navathe, 2008). These architectural limitations of operational databases led to the development of the Data Warehouse approach, which integrates data from different organizational systems into a central structure, provides historical depth, and is optimized for analytical queries (Inmon, 2002).

Another important issue in file-based data management is maintaining data quality. In file formats that lack strict validation and constraint rules at the schema level, violations of data types, value ranges, or logical dependencies may result in *"data pollution"* (Saha & Srivastava, 2014). For example, detecting and correcting errors such as entering a

textual value into a variable that should contain numerical values may require additional checks by users. This situation makes it difficult to maintain data integrity, especially in large datasets created by different users.

File-based data management systems have significant limitations in terms of concurrent access mechanisms. When multiple users work on the same data file at the same time, updates may conflict with each other, data may be overwritten, and uncontrolled file versions may be created over time (Silberschatz et al., 2020; Weidmann, 2023). This situation leads to important consistency and reliability problems, such as determining which file contains the most recent data, who made the changes, and which version of the data should be used in analytical processes (Elmasri & Navathe, 2008; Coronel & Morris, 2015).

The increasing volume of data and the growing variety of data sources have made the limitations of traditional relational databases and Data Warehouse architectures more visible, particularly in terms of scalability, data processing capacity, and data variety. The predefined schema-based structure of relational systems provides important advantages for managing structured data in an organized and consistent way. However, it may create various difficulties in managing unstructured or semi-structured data such as text, images, videos, sensor data, and log records. In addition, storing and processing large volumes of data in centralized systems requires more computing resources and may challenge the scalability limits of traditional systems (Gandomi & Haider, 2015; Stonebraker et al., 2010).

In the Data Warehouse approach, integrating data from different sources into a centralized structure by transforming it into a specific data model has been an important development for organizational reporting and decision-support processes. However, the rapid increase in data volume, the generation of data from different sources and in different formats, and the need to process data in real time or near real time in some use cases have created new requirements that traditional data management approaches alone cannot fully meet. This transformation, particularly

described by the dimensions of volume, velocity, and variety, has increased the need for methods such as distributed storage and parallel processing in data management (Gandomi & Haider, 2015; Laney, 2001) .

The limitations of file-based data management, such as data redundancy, inconsistency, concurrent access, and data integrity issues, increased the need to manage data in a more systematic structure. In response to this need, relational database management systems enabled data to be stored and queried within defined schemas and relationships and to be managed reliably by multiple users (Codd, 1970; Silberschatz et al., 2020). However, the increasing number of operational systems used in organizations and the growing amount of data generated by these systems created new requirements for integrating data from different sources and performing analytical queries on historical data. These requirements supported the development of centralized data structures for decision support and analytical purposes beyond operational data management and contributed to the growing importance of the Data Warehouse approach (Inmon, 2002; Kimball & Ross, 2002).

2.2. Data Warehouse Architecture and Key Features

The increasing variety of operational systems and data sources used in organizations has increased the need to integrate and analyze data generated by different systems. A Data Warehouse is a data management structure in which data obtained from different and heterogeneous sources is integrated, stored, and analyzed for decision-support purposes (Dhaouadi et al., 2022). Data Warehouses have developed as data management systems that support the integration of structured organizational data and its use for analytical purposes (Nambiar & Mundra, 2022). These systems enable data obtained from different sources to be used in decision-support and analytical processes, making them one of the main data infrastructures for Business Intelligence (BI) applications (Antunes et al., 2022; Nambiar & Mundra, 2022). In other words, the main purpose of a Data Warehouse is not to perform daily operations, but to

bring together data generated from different sources and support the analysis of an organization's past and current situation.

At this point, the main difference between operational systems and Data Warehouses can be explained through the concepts of OLTP (Online Transaction Processing) and OLAP (Online Analytical Processing). OLTP systems focus on performing daily operations such as creating orders, recording payments, or updating inventory, while OLAP systems support queries for analyzing and comparing data collected over different periods (Chaudhuri & Dayal, 1997). For example, recording a sales transaction made by a customer is an operational process, whereas comparing sales over the last five years by product, customer, or region is an analytical process. Therefore, Data Warehouses enable data generated in operational systems to be evaluated beyond the context of daily transactions, analyzed over a broader time period, and used for decision-support purposes (Inmon, 2002).

To use data from different operational systems in a Data Warehouse, the data must first be transformed into a common and consistent structure. This process is called ETL (Extract, Transform, Load) and is one of the main components of Data Warehouse architecture (Dhaouadi et al., 2022). In the Extract stage, data is collected from different source systems. In the Transform stage, cleaning, transformation, and integration processes are applied, while in the Load stage, the prepared data is transferred to the Data Warehouse. In this way, an integrated data structure is created, allowing data from different formats or systems to be used together for analytical purposes (Vassiliadis, 2009).

In a traditional Data Warehouse architecture, data flow generally consists of sequential layers, including data sources, the ETL process, the central Data Warehouse, and analytical applications. Data obtained from operational systems is processed through ETL and then integrated into the central Data Warehouse. The stored data is made available to users for analysis through OLAP, Business Intelligence (BI), and reporting tools (Chaudhuri & Dayal, 1997). Smaller data sets created from the organization-wide Data Warehouse to meet the needs of a specific

department or business area are called Data Marts (Inmon, 2002). This structure makes it possible to analyze organizational data distributed across different systems within a common analytical environment. The data flow and the main components of a traditional Data Warehouse architecture are illustrated in Figure 1.

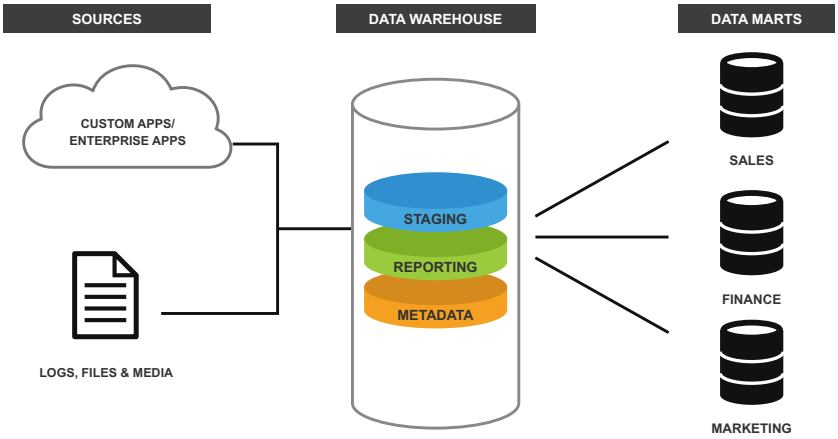


Figure 1. Data flow in traditional data warehouse architecture
Source: Created by the author

The main advantage of this architecture is that data from different sources can be integrated into a common structure and analyzed together with historical data. In this way, organizations can evaluate not only their current operational situation but also changes that occur over time, supporting data-driven decision-making processes. However, since traditional Data Warehouses mainly rely on predefined schemas and structured data, they have faced new requirements as data volume and variety have increased (Nambiar & Mundra, 2022).

In particular, the increasing use of semi-structured and unstructured data, such as text, log, and sensor data, has made the limitations of traditional Data Warehouses in managing different data types more visible. In addition, traditional ETL processes are generally performed at predefined time intervals, which may cause delays in transferring newly generated data from operational systems to analytical environments (de Assis Vilela et al., 2023). As data volume and variety increased and the need for faster analysis became more important, the

demand for more flexible and scalable data management approaches alongside the traditional Data Warehouse approach also increased. These requirements contributed to the later development of Big Data technologies and new data architectures such as Data Lakes.

2.3. Big Data and Data Lakes

Technological developments have also brought major industrial transformations. In particular, with the industry 4.0 movement, which gained momentum from the 2010s onward, the transformation of technological infrastructure became more visible (Nergiz & Barutcu, 2020). One of the most critical components of this transformation has been Big Data. As a result of technological advances and the trends created by these advances across different sectors, approaches to data and methods of processing data have changed significantly (Harby & Zulkernine, 2022). Especially after the 2000s, the increasing amount of data and efforts to analyze this data to obtain meaningful information led to the emergence of the concept of Big Data. In this context, the Big Data approach and related technologies have enabled an important transformation in the production, collection, and processing of data (Mayer-Schönberger & Cukier, 2013).

Considering the developments over the last two decades, it can be stated that this transformation has mainly resulted from the limitations of traditional databases in handling data types that require different processing methods, such as structured, semi-structured, and unstructured data, as well as the need to manage data arriving at different speeds (Hariri et al., 2019). Another critical factor is the limited physical hardware capacity for traditional data analytics processes such as ETL and the inability of established database systems to effectively support high-speed data ingestion (Armbrust et al., 2021). In this context, the concept of Big Data is defined through the 5V model, which addresses these technical needs and challenges: Volume refers to the large amount of data, Velocity represents the speed at which data is generated and processed, Variety refers to the presence of different data formats, Veracity represents the

reliability of data, and Value refers to the strategic benefit obtained from these processes (Demchenko et al., 2014).

The Big Data era has introduced new challenges for Data Warehouses. High-speed and complex data structures continuously generated by industrial facilities, smart production lines, and Internet of Things (IoT/IIoT) ecosystems have significantly limited the processing capacity of traditional Data Warehouse and ETL architectures (Harby & Zulkernine, 2022). As a result, real-time data processing has become necessary for industrial decision-support mechanisms and autonomous process control. However, it can be stated that even technological advances in hardware infrastructure have remained insufficient to enable traditional Data Warehouse systems, which are mainly designed to store filtered and structured data, to manage such dynamic data efficiently.

To overcome these limitations and structural constraints of traditional warehouse architectures, the Data Lake (DL) concept emerged over time. Data Lakes became one of the first flexible storage solutions of the Big Data era by allowing heterogeneous and hybrid unstructured data to be stored rapidly in its raw form without prior transformation, based on the schema-on-read approach. This solution is fundamentally based on an approach in which data is stored without first being converted into a fixed schema, and its structure (schema) is determined only when the data is accessed and analyzed (Janković et al., 2018). The Schema-on-Read approach and its role in big data processing are illustrated in Figure 2.

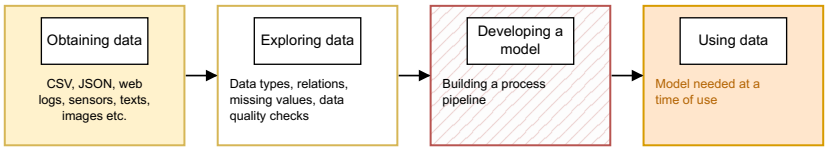


Figure 2. Schema on Read in Big Data Processing
Source: Adapted from Janković et al., 2018

This approach can be illustrated through a global coffee chain or a manufacturing facility. For example, heterogeneous data generated from the point-of-sale systems, mobile application, and IoT sensors in coffee machines of a global coffee chain can be transferred to a Data Lake in its

raw form without a predefined schema requirement. While a supply chain manager defines an analytical schema when accessing this data for inventory forecasting, a regional manager reads the same raw data through a different schema that focuses only on sales performance. Similarly, in a manufacturing facility, vibration, temperature, and camera data generated by machines can be stored in the Data Lake in their raw form. While a predictive maintenance specialist creates a schema suitable for time-series data, a quality control analyst analyzes the same raw data by defining a different schema that includes only visual features.

In both scenarios, heterogeneous raw data continuously generated from different sources and geographical locations is transferred through the network layer without any prior processing or transformation. The data is then written and stored in its raw form at high speed on the physical disk blocks of low-cost commodity hardware clusters operating in a distributed architecture or in highly scalable cloud object storage systems.

Data Lakes allow data from a wide variety of sources, such as OLTP systems, Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), cloud services, social media, and IoT sensor records, to be stored in their original raw formats without requiring any prior transformation or formatting (Janssen et al., 2024). The removal of complex and time-consuming ETL processes before data ingestion significantly reduces initial storage costs (Khine & Wang, 2018). In particular, distributed file system architectures such as Hadoop, which are based on low-cost infrastructure, are used to store data in its raw form for later processing (HDFS Architecture Guide, n.d.). In addition, the ability to query data using specific schemas according to analytical needs at the time of reading (schema-on-read) makes it easier for authorized users and data scientists within an organization to directly access data through different analytical tools for a wide range of use cases, including machine learning models (Azzabi et al., 2024; Walker & Alrehamy, 2015). The conceptual architecture of a Data Lake, including its data ingestion, storage, and analytical components, is illustrated in Figure 3.

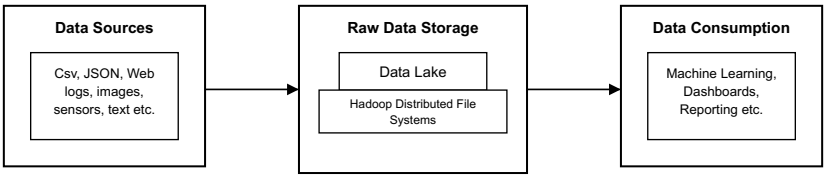


Figure 3. Data Lake Conceptual Architecture
Source: Created by the author

However, this high level of storage flexibility and ease of raw data ingestion also brings several methodological and operational challenges. Storing data without a predefined schema may lead to lower data quality, make it more difficult to track changing data structures, and create a continuous need for metadata extraction to transform the data. At the same time, millions of small files created in storage by continuous and fragmented data streams, such as IoT sensor data and logs, may cause the small file problem. This increases file system metadata overhead, slows down read/write (I/O) operations, and significantly reduces analytical query performance. Data Lakes that are not supported by effective metadata management, strong data governance, and security measures may result in delays in raw data processing, the accumulation of stale data, and inefficient use of resources. In such an uncontrolled environment, the reliability of data analytics processes may decrease, causing Data Lakes to lose their functionality and turn into "Data Swamps" (Gali et al., 2022; Janssen et al., 2024; Khine & Wang, 2018).

These limitations experienced in Data Lakes have become one of the main factors leading to the emergence of the Data Lakehouse architecture, which combines Atomicity, Consistency, Isolation, and Durability (ACID) reliability with the flexibility of Data Lakes within a single architecture.

2.4 From Data Lakes to Data Lakehouses

In today's data architectures, particularly in large organizations, traditional Data Warehouses and Data Lakes alone may be insufficient to meet the requirements of modern data analytics, machine learning, and real-time data processing due to the previously discussed limitations. This

limitation has led to the emergence of the Data Lakehouse architecture, which combines the strengths of both approaches within a single structure.

Open Table Formats form the technical foundation of the transition from Data Lake to Data Lakehouse architecture. Open Table Formats such as Delta Lake, Apache Iceberg, and Apache Hudi aim to provide relational database capabilities directly at the object storage level by building an ACID-compliant logical transaction log layer on top of cloud object storage (Parimi, 2025).

At the center of the transition architecture is the Medallion Architecture, in which data is processed gradually according to its quality. The data flow starts in the Bronze layer, where raw data is accepted in its original source format with schema-on-read flexibility. It then moves to the Silver layer, where data is cleaned, data types are validated, and schema enforcement rules are applied. Finally, the data is transferred to the Gold layer, where it is aggregated into star schemas for Business Intelligence and advanced analytical models, supporting end-to-end data quality (Schneider et al., 2024). Figure 4 presents this layered architecture, highlighting how data is progressively transformed from raw inputs into refined datasets suitable for analytical applications.

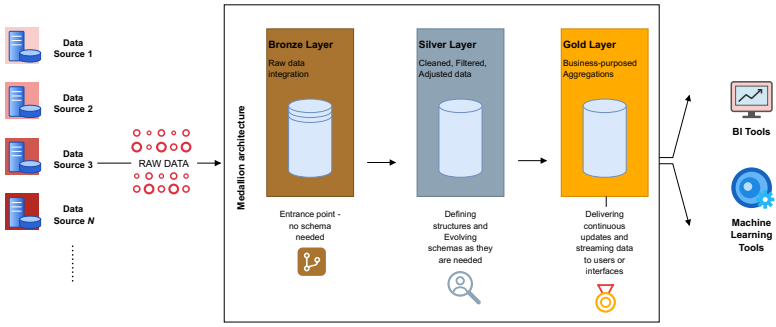


Figure 4. Lakehouse and Medallion Architecture
Source: Created by the author

In the implementation process, the transformation begins by handling text-based raw data that initially arrives in the Data Lake, such as CSV, JSON, logs, and sensor data, together with data that has already been

converted into columnar formats such as Parquet and ORC (Optimized Row Columnar), which provide high compression rates to improve analytical performance and reduce storage requirements (Armbrust et al., 2021). Unlike traditional text files, these columnar structured formats store data column by column rather than row by row. This allows only the relevant columns to be read from very large datasets and significantly reduces analytical query times.

Data already stored in the system in Parquet or ORC format can be quickly converted to next-generation table formats, such as Delta Lake and Apache Iceberg, by updating only the metadata layer through in-place conversion, without the cost of copying the data from the beginning. Raw streaming data, such as CSV and JSON, is directly ingested into the raw (Bronze) layer of the architecture and connected to automated transformation pipelines through ACID-supported table formats.

After this integration is completed, the *"small file problem",* one of the main challenges of Data Lakes, is addressed by combining fragmented files into appropriate sizes through compaction/optimization. By physically organizing data according to frequently queried columns using Z-Ordering or multi-dimensional clustering, the system can directly skip unrelated data blocks during query execution through data skipping, which significantly improves read performance. In addition, the storage overhead created over time by the transaction history, which records each change, and the time travel feature, which provides access to previous versions, is managed by periodically removing old versions through vacuuming (Databricks, n.d.; Delta Lake, n.d.).

As a result, the evolution from Data Warehouse to Data Lake and, more recently, to Data Lakehouse is not simply a change in storage methods or file formats. This transformation represents a comprehensive architectural development that provides end-to-end data quality across both raw and processed data flows, row- and column-level access security, flexible schema changes (schema evolution), and control over the source and movement of data (data lineage). The main characteristics, key capabilities, and operational differences of these three architectural

approaches are presented in detail in the comparison table (Table 1), which summarizes the main points discussed in this section. The main characteristics, key capabilities, and operational differences of these four architectural approaches are summarized in Table 1, highlighting the key distinctions discussed in this section.

Table 1. Comparison of all architectures

	Traditional Data Management	**Data Warehouse**	**Data Lake**	**Data Lakehouse**
Main Purpose	Managing daily operational transactions	Reporting and data analysis	Storing large volumes of raw data	Integrating data management, BI, and advanced analytics
Schema Approach	Schema-on-Write	Schema-on-Write	Schema-on-Read	Schema-on-Read and Schema-on-Write
Data Processing	Database operations	ETL/ELT and analytical processing (OLAP)	Data is stored first and processed later	Step-by-step processing with Medallion Architecture (Bronze–Silver–Gold)
Data Reliability	High	High	Can be difficult to manage	Supports ACID transactions
Performance	Effective for operational transactions	Suitable for analytical queries	Depends on processing engines, data formats, and optimization techniques	Can be optimized for analytical queries
Storage	Databases and file systems	On-premises, cloud, or distributed data warehouse storage	Distributed or cloud storage	Commonly cloud object storage with managed table formats
Cost	Increases as data volume grows	Relatively high	Relatively low	More flexible in terms of storage costs

3. Big Data Applications and Technologies

In today's digital ecosystem, the effective storage, processing, and analysis of rapidly growing data volumes have caused traditional database systems and hardware infrastructures to face various limitations in terms

of capacity and scalability. In this context, Big Data Management (BDM) approaches are becoming increasingly integrated with cloud computing infrastructures that support scalable and flexible resource use (Qi et al., 2023). Cloud computing platforms provide infrastructure, platform, and analytical services through service-based models, allowing organizations to respond dynamically to changing data and processing requirements. With these features, cloud-based Big Data solutions have become an important technological infrastructure in both academic and industrial applications for managing data-intensive processes and supporting data-driven decision-making mechanisms (Berisha et al., 2022).

3.1. Cloud-Based Big Data Platforms

Cloud-based Big Data platforms provide scalable storage and parallel processing capabilities for businesses, healthcare organizations, smart cities, and educational infrastructures. The increasing use of Big Data analytics in cloud environments has also increased the adoption of the ELT approach alongside the traditional ETL approach (Berisha et al., 2022).

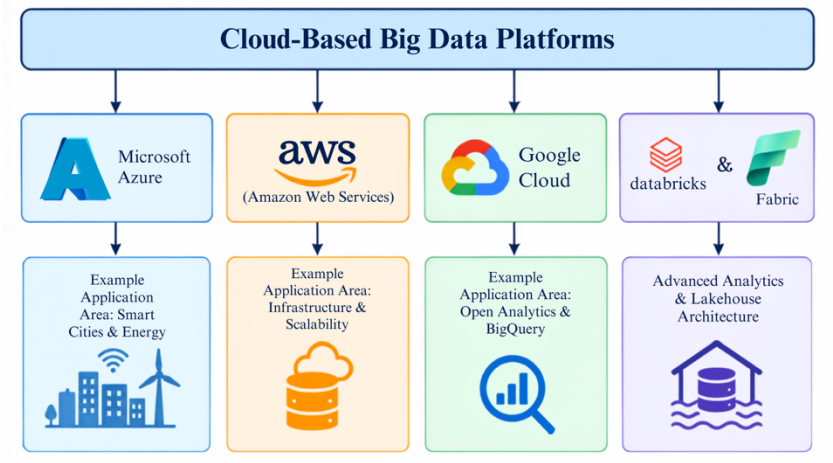


Figure 5. Cloud-base big data platforms
Source: Created by the author

As shown in Figure 5, today's cloud-based Big Data ecosystem includes large-scale cloud service providers such as Microsoft Azure,

Amazon Web Services (AWS), and Google Cloud, as well as integrated data and analytics platforms such as Databricks and Microsoft Fabric. These platforms support scalable data storage, distributed data processing, and analytical services in cloud environments. The ability to scale cloud-based resources according to changing requirements allows organizations to manage Big Data workloads of different volumes and characteristics more flexibly (Berisha et al., 2022; Qi et al., 2023). BigQuery, which is part of the Google Cloud ecosystem, is one of the cloud-based Data Warehouse solutions that enables large-scale datasets to be analyzed through a serverless architecture (Berisha et al., 2022).

The development of cloud-based data platforms has transformed architectures not only for storing Big Data but also for processing and analyzing data from different sources in an integrated way. In particular, the Data Lake approach allows structured, semi-structured, and unstructured data to be stored in their original formats. This structure reduces the need to transform data into a predefined schema in advance and makes it easier to meet different analytical requirements using the same data source (Berisha et al., 2022).

One important result of this transformation is the emergence of the Lakehouse architecture, which combines the strengths of Data Lake and Data Warehouse approaches. The Lakehouse architecture aims to combine the flexible and scalable storage structure of Data Lakes with the data management and analytical capabilities of Data Warehouses. In this way, Business Intelligence applications, data science processes, and machine learning workloads can be performed on a common data infrastructure (Armbrust et al., 2021). While Databricks is one of the leading platforms in the development and adoption of this architecture, Microsoft Fabric is also a current platform that brings together data engineering, data science, real-time analytics, and Business Intelligence processes within an integrated analytics environment.

This integrated structure provided by cloud-based Big Data platforms allows organizations to manage large volumes of data from different sources more flexibly and to scale analytical processes according

to changing requirements. However, the effectiveness of Big Data infrastructure depends not only on where the data is stored but also on how quickly and efficiently it is processed using different technologies. Therefore, distributed and real-time data processing technologies such as Apache Spark and Apache Kafka represent another important component of the modern big data ecosystem.

3.2. Big Data Processing Technologies

Traditional batch processing methods and disk-based architectures such as MapReduce face various limitations, particularly in Big Data applications that require low latency and real-time analytics. For this reason, in-memory computing, distributed computing, and stream processing approaches have become increasingly important in modern Big Data systems. Apache Spark is one of the main technologies in this transformation and enables large datasets to be processed in parallel and distributed across computer clusters (Belcastro et al., 2022). Spark's in-memory processing capabilities can provide important advantages over the disk-based MapReduce approach, especially for iterative and interactive analytical workloads.

Resilient Distributed Dataset (RDD), one of Spark's main data abstractions, supports the distributed processing of data across cluster nodes in a parallel and fault-tolerant manner. Within the Spark ecosystem, Spark SQL enables structured data to be processed through SQL queries, Datasets, and DataFrames, while MLlib supports the scalable application of machine learning methods such as classification, regression, and clustering on large datasets. Spark Streaming enables the same ecosystem to process streaming data (Belcastro et al., 2022).

Real-time stream processing technologies are especially important for analyzing continuously generated data such as IoT sensor data, system logs, financial transactions, and social media streams. In these architectures, Apache Kafka is a distributed messaging and event-streaming platform that supports the collection of high-volume data streams from different sources and their transfer to distributed systems.

Data transferred through Kafka can be processed by distributed processing engines such as Spark Structured Streaming or Apache Flink and included in real-time analytical processes (Lalaoui et al., 2025).

The integrated use of these technologies enables data collection, transmission, distributed processing, and analytics to be carried out within an end-to-end data pipeline. In this way, high-volume data streams can be processed with low latency and used in time-sensitive applications such as real-time analytics and decision support (Isah et al., 2019). However, the ability of Big Data to create value for organizations depends not only on processing data quickly and in a scalable way but also on transforming the results into understandable information and using them in decision-making processes. At this point, Business Intelligence systems play an important role in presenting analytical results generated by Big Data infrastructures to decision-makers through dashboards, reporting tools, real-time decision-support systems, and enterprise analytics applications.

3.3. Big Data and Business Intelligence

The development of Big Data technologies has enabled organizations not only to store large volumes and various types of data obtained from different sources but also to analyze this data and use it in decision-making processes. In this context, Business Intelligence (BI) includes the methods, processes, and technologies used to analyze data and transform it into meaningful and useful information for managers and decision-makers. The integration of Big Data and Business Intelligence supports moving beyond traditional reporting approaches and enables more comprehensive analytical processes (Phillips-Wren et al., 2021; Wang et al., 2022).

One of the important components of Business Intelligence applications is dashboards. Dashboards are Business Intelligence tools that support the monitoring of Key Performance Indicators (KPIs), trends, and analytical results through charts and tables. Reporting systems contribute to presenting operational and managerial data in a form that can be used in decision-making processes (Martins et al., 2022).

The rapid data processing capabilities provided by Big Data infrastructures have contributed to the transformation of Business Intelligence applications from systems based only on the analysis of historical data into more dynamic systems. In particular, transferring continuously generated data to analytical systems enables the development of real-time decision support processes. Through these systems, organizations can monitor operational changes more quickly, identify unusual situations, and use up-to-date analytical results in decision-making processes. This development has contributed to the expansion of Business Intelligence beyond the reporting of historical data to include analytical applications that support decision-making processes using more current data (Phillips-Wren et al., 2021; Wang et al., 2022).

Another result of this development is the increasing use of enterprise analytics applications. Enterprise analytics refers to the integrated analysis of different organizational data sources and their use in performance evaluation and decision-support processes (Martins et al., 2022; Wang et al., 2022).

However, the increasing volume and variety of data have made it necessary for organizations not only to analyze current and historical situations but also to predict future situations and identify complex data patterns. This need has accelerated the integration of Big Data analytics with machine learning and artificial intelligence methods. As a result, the Big Data ecosystem is expanding from reporting and visualization toward predictive analytics, automated decision-making, and generative artificial intelligence applications. This transformation makes it necessary to examine the relationship between Big Data and artificial intelligence.

3.4. Big Data and Artificial Intelligence

Big Data and Artificial Intelligence (AI) are considered two key technology areas that complement each other in today's data-driven systems. Large volumes of diverse and continuously generated data provide an important resource for developing and training AI models, while AI methods make it possible to identify complex relationships and

patterns within these datasets. In this context, machine learning is used for analytical tasks such as classification, clustering, prediction, and anomaly detection, while Deep Learning (DL) is particularly important for analyzing high-dimensional and unstructured data such as text, images, and audio. The integration of Big Data processing infrastructures with AI methods supports the scalable application of these models to larger datasets (Rahmani et al., 2021).

One of the important application areas where Big Data and Artificial Intelligence are integrated is predictive analytics. Predictive analytics aims to predict future events, trends, or behaviors based on patterns obtained from historical and current data. This approach can be used in data-intensive applications such as demand forecasting, risk assessment, customer behavior prediction, anomaly and fraud detection, and predictive maintenance. Therefore, AI-supported Big Data analytics goes beyond traditional descriptive analytics by providing a more advanced analytical structure that enables predictions to be generated from data and supports decision-making processes (Rahmani et al., 2021).

In recent years, the development of generative artificial intelligence and large language models has expanded the use of Big Data beyond prediction and classification toward the generation of new content and information (Banh & Strobel, 2023). One important application of this development is the retrieval-augmented generation approach, which supports generative models with relevant content obtained from external information sources. In a RAG architecture, information related to a user query is first obtained through retrieval from organizational documents, databases, or other information sources and is then provided to the generative model as context. In this way, connections can be established between organizational information sources within Big Data ecosystems and Generative AI models, supporting more context-aware information retrieval and generation (Gao et al., 2024).

4. Current State and Future Trends

Data Lakes provide flexibility for storing large-scale data with different structures and formats; however, they also involve various technical and operational limitations during implementation and operation. In particular, storing unstructured raw data without sufficient prior validation may make it more difficult to ensure data consistency and accuracy and may cause data quality problems (Laurent et al., 2020). In addition, the development and implementation of data governance policies require additional time and cost. The absence of standardized schemas or data models may make it more difficult to integrate data from heterogeneous sources, while providing access to large user groups raises important considerations regarding data security and privacy (Marjani et al., 2017).

One of these challenges is the risk of Data Lakes turning into a *"Data Swamp"* over time. Insufficient information about data types, data quality, and data lineage may make stored data more difficult to understand and use (Azzabi et al., 2024). In this context, metadata management is considered an important component. Associating metadata with data during data ingestion is important for identifying and tracking data and applying access policies. However, effective metadata management may require the integration of the Data Lake with existing metadata tools and the tracking of data transformations performed at different stages (Marz & Warren, 2015). At the organizational level, integrating different databases, systems, and data silos, automating processes, and applying governance standards is a process that requires technical expertise (Azzabi et al., 2024).

In addition to these technical and management challenges in Data Lakes, recent studies also examine the relationship between data management and Artificial Intelligence and Machine Learning applications. In this context, improving existing Data Lake functions and supporting Machine Learning applications in these environments are considered among the topics that can be explored in future research. While examining the existing functions and open research problems of

Data Lake systems, Hai et al. (2023) identify supporting Machine Learning in Data Lakes as one of the areas for future research. In parallel, there are also studies focusing on the storage of high-dimensional data structures used in Artificial Intelligence and Machine Learning applications. Bao et al. (2024) propose the Delta Tensor approach for more efficient storage of vector and tensor data in a Delta Lake-based Lakehouse architecture and show through experiments that improvements in time and storage space can be achieved compared with traditional tensor serialization methods. These studies indicate that, in addition to existing challenges related to data quality, governance, metadata management, and integration, the management of data structures required by Machine Learning applications is also among the current research topics for Data Lakes and related data architectures.

As a result, in addition to existing issues such as data governance, metadata management, and data quality, the management of data structures required by Machine Learning applications is also among the topics that can be addressed in future research on Data Lakes and Lakehouse architectures.

5. Conclusion

The evolution of big data architectures reflects the growing demand for scalable, flexible, and integrated data management approaches capable of accommodating diverse data types and analytical requirements. The transition from traditional data warehouses to data lakes and subsequently to Data Lakehouse architectures represents a significant development in managing large-scale and heterogeneous datasets. By combining the structured data management capabilities of data warehouses with the flexibility of data lakes, the Data Lakehouse approach provides a unified architectural framework for supporting different data formats and analytical workloads (Armbrust et al., 2021; Harby & Zulkernine, 2022).

The integration of distributed data processing technologies into modern data architectures represents another important advancement in managing and analyzing complex datasets. In particular, scalable

processing frameworks support large-scale data analytics by addressing increasing data volumes and computational demands (Belcastro et al., 2022). Within this context, Data Lakehouse architectures offer opportunities to integrate data storage, processing, and analytical capabilities within a common environment. However, their successful implementation requires careful consideration of system design, technological compatibility, and infrastructure requirements (Schneider et al., 2024).

Despite these developments, several challenges remain, particularly in relation to data governance, interoperability, architectural complexity, and the management of heterogeneous data environments. Ensuring data security, maintaining data integrity, and integrating diverse data sources within a unified infrastructure continue to be important considerations for the sustainability of modern data architectures (Janssen et al., 2024). Accordingly, future research should further investigate the applicability of Data Lakehouse architectures across different operational environments, with particular emphasis on comparative evaluations of scalability, processing efficiency, data reliability, and organizational requirements.

Overall, the transition toward Data Lakehouse architectures represents an important stage in the ongoing evolution of big data management technologies. Rather than completely replacing traditional data management approaches, these architectures provide an alternative model that integrates the strengths of existing systems with contemporary analytical requirements. The integration of data storage and processing capabilities within a unified architectural framework offers opportunities for developing more flexible, reliable, and interconnected data ecosystems. In this regard, the continued development of Data Lakehouse architectures is expected to play an important role in supporting increasingly complex data-driven applications and shaping the future of big data infrastructure (Armbrust et al., 2021; Schneider et al., 2024).

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, ChatGPT (OpenAI) was used for language review in selected sections. The ChatGPT–Canva integration was also used during the preparation of Figure 5, with subsequent visual editing and final adjustments carried out by the author in Canva. The author retains full responsibility for the content of the chapter.

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Chapter 11:

Digital Literacy: A Conceptual Review of Concepts, Skills and Models from the Perspective of Digital Transformation and Technology and Innovation Management

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Abstract

As information and communication technologies reshape every field from education to business, digital literacy is increasingly regarded as one of the basic conditions for individuals and organizations to adapt to digital transformation. This book chapter is a conceptual review that examines digital literacy in an integrated way through its definitions, its relationship with education, its developmental levels, its component skills and its theoretical models. The chapter first evaluates the terminological development of the concept since its first use and the research focusing on teachers; it then discusses the three-stage approach consisting of digital competence, digital usage and digital transformation, together with the components of information, media and technology literacy. The common and diverging aspects of different models are compared, and the boundaries with sub-disciplines such as computer, library, internet, information, media, electronic information and digital information literacy are examined. The review shows that definitions have expanded from technical skills toward cognitive and socio-ethical dimensions, while research has largely concentrated on determining levels. It is therefore argued that the highest level of digital literacy, which is linked to creativity and innovation, deserves more attention from a technology and innovation management perspective. The chapter closes with recommendations for practice and future research.

Keywords: digital literacy, digital transformation, digital competence, technology and innovation management, teacher education

1. Introduction

In the twenty-first century, information and communication technologies have permeated every layer of society, and taking part in this digital world requires competencies beyond basic literacy. Conceptualized by Paul Gilster in 1997 (Gilster, 1997, as cited in Belshaw, 2012), digital literacy is not merely the ability to operate technical devices; it is also the competence to evaluate information in digital environments critically, to synthesize it and to reproduce it in line with ethical values. In education in particular, teachers' possession of this competence is a strategic factor in how well new generations adapt to digital transformation. The following sections examine the terminological development of digital literacy and its organic link with education. They then elaborate the theoretical models that address the technical, cognitive and social dimensions of the concept and present the levels, components and sub-disciplines of this complex skill set within a theoretical framework.

Despite its wide use, there is no consensus on a single definition of the concept in the literature. Some authors treat digital literacy as the ability to evaluate information, others as a set of skills that makes it possible to survive in the digital age, and others as the competence to use technology safely and ethically. The proliferation of proposals on levels, skills and models has increased this diversity further and left open the question of which framework researchers should adopt.

The aim of this chapter is to bring these scattered approaches together in a single conceptual framework and to discuss digital literacy by relating it to core concepts of the management information systems field, such as digital transformation and technology and innovation management. The chapter is a conceptual review; it does not collect new data but interprets the existing literature. It can also be read as a complementary review that broadens the theoretical ground for the author's doctoral dissertation (Temel, 2025), and for the joint study derived from it, which is in press (Temel & Gündüzyeli, in press).

The second section presents the definitions and terminological development of the concept, and the third section addresses its

relationship with education. The fourth and fifth sections cover developmental levels and component skills, the sixth section covers theoretical models, and the seventh section covers sub-disciplines. The eighth section discusses the reviewed literature as a whole, the ninth section states the limitations, the tenth section offers recommendations, and the eleventh section concludes the chapter.

2. The Concept and Definition of Digital Literacy

The entry of the concept into academic literature is associated with Paul Gilster's work (Gilster, 1997, as cited in Belshaw, 2012). Gilster regarded digital literacy as the capacity to grasp and evaluate information presented in different formats and to bring that information together, and he grouped the content of the concept under the activities of internet searching, hypertext navigation, knowledge assembly and content evaluation (Bawden, 2008).

The advance of digital technologies is one of the cornerstones of today's societies and of human development throughout history. At the basis of this process lies the concept of "digital," which is defined as the expression of data in numbers in electronic devices.

Martin (2006) defines digital literacy as individuals' ability to recognize, access, use, combine, evaluate, analyze and synthesize digital materials, and to use technological tools to reach new information through these skills.

Later authors have extended this core from different directions. While Hague and Payton (2010) place the focus on the correct and safe use of technology, Eshet-Alkalai (2004) sees the concept as a condition of surviving in the digital age. Ferrari (2012) includes in the definition understanding media, finding and critically evaluating stored information, and interacting through various communication tools. According to Bawden (2008), the concept is the set of skills that enables an individual to complete tasks in the digital environment successfully.

Besides covering the efficient use of mass communication tools, digital literacy can also be described as acquiring the abilities to use technologies safely and in line with moral norms and laws, for individual development, problem solving and benefit in social activities (Özerbaş & Kuralbayeva, 2018).

Digital literacy mediates the appropriate use of information once its source has been reached, and its importance in educational activities continues to grow. The literature shows that many countries, such as England and Scotland, have recognized the need to raise generations with high digital literacy and have added digital literacy topics to their curricula (The Royal Society, 2012).

Steps to spread the concept have also been taken in Türkiye. According to an announcement by the Yükseköğretim Kurulu, training was given to academic staff in some provinces and a Digital Literacy course was added to the curricula of these provinces. A news report on the same project states that more than 30,000 students at eight pilot universities took the digital literacy course (Anadolu Ajansı, 2019).

Kaya-Özgül et al. (2023) found in their study that digital literacy levels were higher among male teachers than female teachers, younger teachers than older teachers, experienced teachers than inexperienced ones, teachers in private schools than those in state schools, teachers with postgraduate education than those with a bachelor's degree, and teachers who own a personal computer or tablet than those who do not.

The same study also compared the digital literacy levels of classroom teachers in state and private schools, and concluded that factors such as the greater technological resources of private schools and their more frequent use might enable teachers in private schools to be more knowledgeable on the subject and to develop themselves. Furthermore, they were found to be open to evaluating technological opportunities and to hold a positive attitude toward the use of technology in education.

The embedding of digitalization in everyday life has made digital literacy an indispensable skill for individuals (Öztürk & Ateş Kaya, 2023). Because digital technologies are so heavily relied on to find and produce information, students' literacy levels need to be raised to prepare them for the future. The concept is therefore not limited to the use of tools; it should also cover accessing reliable information, producing and sharing information, and using technology in learning and teaching processes (Hamutoğlu et al., 2017).

A review of the research on digital literacy shows that most studies aim to determine the digital literacy levels of teachers and teacher candidates working in different fields (Aksoy et al., 2021; Arslan, 2019; Öztürk & Budak, 2019; Üstündağ et al., 2017; Yaman, 2019; Yontar, 2019).

There are also studies that determine and compare the digital literacy levels of pre-service teachers in different countries such as Kazakhstan (Özerbaş & Kuralbayeva, 2018), and of school administrators (Sönmez & Gül, 2014).

According to Çubukçu and Bayzan (2013), digital literacy holds a more important position than literacy acquired through traditional methods. Individuals who lack the ability to use digital technologies are thought to miss out on many of the opportunities that technology offers.

The widespread use of the many digital platforms that support curricula in education, and the wish to use them even more intensively, make it necessary for teachers to gain competence in this area (Aksoy et al., 2021).

According to the emphasis of Gürtekin (2019), digital literacy is more important than traditional literacy because it stresses not only the ability to use technology but also the abilities to access, produce and share accurate information. This reveals the importance of the ability to use technology effectively in learning and teaching processes.

In today's digital world, digital literacy stands out as a right that enables people's cultural and social participation. Developing students' digital literacy provides them with the skills, knowledge and understanding

they need to take on their future social, cultural, economic, civic and intellectual roles fully and effectively (Hague & Payton, 2010).

Digital literacy is not limited to technical skills; it also includes a wide range of cognitive abilities, from internet use to user interfaces and communication (Özoğlu, 2019).

3. Digital Literacy and Education

According to Kara and Atasoy (2019), the greatest effect of technological advances today is felt in the field of education. They note that children meet the digital world, especially the internet, before starting school.

Digital literacy enables young people to benefit from the opportunities technology offers while also encouraging them to be careful about possible risks. As digital technology and media become more central to social life, young people's knowledge, skills and understanding in this area will become more decisive (Hague & Payton, 2010).

As Tulay (2019) states, integrating technology into the educational process makes teachers its main supporters. This approach directs teachers toward a student-centered perspective and helps them encourage transformation in education inside and outside the classroom.

Digital literacy skills contribute to students' critical thinking and increase their integration with technology. They also facilitate access to reliable information, develop effective virtual communication skills and encourage conscious internet use. In addition to enabling the effective use of traditional and social media platforms, they develop the abilities to interpret, analyze and reproduce information. By giving students operational and technical knowledge and skills, they support the educational use of digital media (Taşkıran & Salur, 2021).

Cabı (2016) argues that digital technology affects education and teaching just as it affects every area of life. Karabacak and Sezgin (2019) note that the science of education is undergoing significant changes on the basis of people, knowledge and society. Kuru (2019) agrees with these

views and emphasizes that the twenty-first century is defined as the age of knowledge and technology and that information technologies shape the learning-teaching process.

As Cebeci (2020) states, digital literacy is also seen as a skill that requires the ability to bring different pieces together to create new products from existing information by using digital tools. The growing use of technology and digital tools in educational settings therefore increases the importance and necessity of digital literacy.

Teachers must be able to use information technologies at a level that meets the educational requirements of the twenty-first century. They are also expected to be competent in their own fields of expertise, to use appropriate teaching methods and techniques, and to participate actively. This requires technological and pedagogical competence together with content knowledge (Yükseltürk et al., 2017).

Education should give young people the skills to understand and use the digital world. It is therefore important for twenty-first-century teachers to have digital competencies. Research shows that it is difficult for teachers who lack digital competencies to raise students who have them (Timur et al., 2014).

4. Levels of Digital Literacy

Martin and Grudziecki (2006) described the developmental process of digital literacy in three stages: digital competence, digital usage and digital transformation. Digital competence refers to the basic skills and attitudes needed in daily life; digital usage refers to applying these competencies in a professional or personal context; and digital transformation refers to using them to create new, innovative practices. Martin (2008) later placed this structure within the wider discussion of the "digital society". The levels are examined in detail in Section 6.4.

5. Digital (Information, Media and Technology) Literacy Skills

Digital literacy includes the active use of information and communication technologies by individuals as well as the important contributions these technologies make to people and society. It is the set of skills and competencies that supports production-oriented and socially collaborative work, together with the ability to solve problems that may arise in any area of life with technology in an ethical, safe and lawful way (Özerbaş & Kuralbayeva, 2018).

Çubukçu and Bayzan (2013) define digital literacy skills as the ability to recognize technology, to use useful technologies effectively, to recognize and access accurate information, and to distinguish true from false information by analyzing it.

Digital literacy skills consist of three main components: information literacy, media literacy and technology literacy (Trilling & Fadel, 2009).

5.1. Information Literacy

Kızıl (2007) states that the existence of individuals who can apply information to their lives in every respect led to the emergence of a concept such as information literacy.

The characteristics of individuals who have the information literacy skills described by the Partnership for 21st Century Learning (2019) are as follows:

a) They should access information by using their time and resources efficiently and effectively,

b) They should be able to evaluate information critically,

c) When they face a problem, they should reach accurate information and use it creatively,

d) They should be able to analyze and manage information obtained from different sources.

5.2. Media Literacy

Media literacy refers to an individual's ability to analyze and filter messages consciously. This skill first requires reaching messages and then examining them by analyzing them. It must then include evaluating these messages and conveying them accurately and meaningfully to the intended person (Karakoyun, 2014).

New media uses associated with the internet and technology are part of media literacy, which includes the ability to consciously create one's own media content and convey it to others, together with the innovations emerging in the individual's life.

5.3. Technology Literacy

Being able to use today's technology has given rise to the concept of technology literacy.

According to Bölükbaşı (2012), technology literacy has four basic competencies. These are:

1. Adapting to continuously and rapidly changing technology and managing this change,
2. Producing innovative solutions to technological problems encountered throughout life,
3. Using technological knowledge effectively and putting it into practice,
4. Wisely analyzing and evaluating the individual and social effects of technology.

6. Digital Literacy Models

The literature contains different conceptual models of digital literacy developed in education such as the Krumsvik (2011) model, the Calvani et al. (2008) model, the Hobbs (2010) model, the Martin (2008) model, the Hague and Payton (2010) model and the Ng (2012) model.

6.1. The Rune Johan Krumsvik Model

Krumsvik (2011) argued that digital literacy skills should first be acquired by educators. He emphasized that traditional teaching methods should be abandoned and digital opportunities used fully and suggested that students' interest and achievement would increase in this way.

The model consists of two axes, horizontal and vertical. The horizontal axis contains digital literacy skills, while the vertical axis contains levels of digital literacy awareness.

The sections between the axes of the model also have a four-layered structure. Basic skills are at the center, the second layer contains the effective use of these skills in lessons, and the third layer contains learning strategies and metacognition. The final layer aims to help teachers understand how digital planning is affected by digital reforms and digitalized schools.

6.2. Calvani, Cartelli, Fini and Ranieri Digital Competence Model

This model includes a person's responsibilities toward themselves and others, as well as the skills of flexibly exploring new technological developments, analyzing accurate data, evaluating critically, anticipating and solving possible problems, and using technological tools effectively for teamwork.

Digital competence is examined in three basic dimensions: technological, cognitive and ethical. The technological dimension covers the ability to use new technologies effectively and flexibly. In the cognitive dimension, the ability to access information and evaluate it is important. The ethical dimension refers to the ability to communicate effectively with an ethical understanding while using information technologies (Calvani et al., 2008).

6.3. The Renee Hobbs Media Literacy Model

Hobbs (2010) stated that media literacy lies at the foundation of digital literacy. This emphasizes that, besides using computer software and benefiting from internet tools, the use of social media is also fundamental to digital literacy. The five competencies in Hobbs's framework are access (finding appropriate and relevant information and sharing it through media texts and technological tools), analysis (using critical thinking to examine a message's purpose, target audience, quality and credibility), creation (producing content with creativity and confidence), reflection (examining the effect of media messages and technological tools on thought and behavior in daily life) and action (sharing knowledge and solving problems individually or collaboratively). When these five competencies support one another, individuals can remain active in both receiving and producing information and continue lifelong learning.

6.4. The Allan Martin Digital Literacy Model

Martin (2008), building on Martin and Grudziecki (2006), describes digital literacy as a model consisting of three main components: digital competence, digital usage and digital transformation.

Digital competence represents the first, basic level. In general, these are the basic characteristics that everyone should have in order to ease daily tasks and keep up with the age.

Digital usage is regarded as the second, intermediate level. It generally advances with the development of basic competencies. It is the level required for people to cope with problems in working life, leisure time or other areas of life.

Digital transformation represents the third, upper level. When the usages developed at the second level enable innovation and creativity, they can stimulate significant change in the professional or knowledge domain, at the level of the individual, the group or the organization. However, transformation is not a necessary condition of digital literacy; appropriate

and informed usage at the second level is sufficient to describe a person as digitally literate (Martin & Grudziecki, 2006).

6.5. The Cassie Hague and Sarah Payton Model

Hague and Payton (2010) define digital literacy as the intersection of eight interrelated components. These components are: functional skills, effective communication, ability to find and select information, critical thinking and evaluation, cultural and social understanding, collaboration, creativity and e-safety. Digital literacy lies at the center of these components.

Web 2.0 tools enable users at every level to easily perform activities such as communication, interaction, information sharing, access to information, collaborative content creation, content storage and sharing, evaluation and visualization. These technological tools encourage students to be active participants in learning environments and to contribute to content (Yükseltürk et al., 2017).

6.6. The Wan Ng Model

The digital literacy model developed by Ng (2012) consists of the intersection of three different dimensions: technical, cognitive and social-emotional.

The technical dimension basically refers to having technical and functional skills. In education and daily work, it includes the ability to use even the smallest pieces of equipment, such as headphones, projectors and smart boards, without difficulty and to work with them effectively. It also covers the ability to study manuals for such devices and to solve problems independently using platforms such as YouTube.

The cognitive dimension concerns the cycle of critical thinking, evaluation and creation in the process of accessing information. It also refers to the ability to evaluate and select suitable software programs to complete a task.

The social-emotional dimension refers to acting with respect and tolerance for effective communication, choosing appropriate words to prevent misunderstandings and communicating with others in a courteous manner.

7. Sub-Disciplines of Digital Literacy

With the rapid advance of digital technology, a different digital literacy need has emerged in every area of daily life. Koltay (2011) listed the literacy sub-disciplines related to digital technologies as follows:

Computer literacy,

Library literacy,

Internet literacy,

Information literacy,

Media literacy,

Electronic information literacy,

Digital information literacy,

However, particularly from the perspectives of digital communication, new media studies and educational technology, these concepts are generally examined within the framework of digital literacy. The focal points of these literacy types, each of which is closely related to digital technologies, may differ from one another, but it is hardly possible to draw a clear distinction among them.

8. Discussion

The reviewed literature shows that definitions of digital literacy have expanded markedly over time. In the concept's first use, the emphasis was on understanding and evaluating information presented in a computer environment (Belshaw, 2012). Later definitions foreground elements such as surviving in the digital era (Eshet-Alkalai, 2004), understanding media and searching for and critiquing information (Ferrari, 2012), and using technology safely (Hague & Payton, 2010). This trajectory suggests that

digital literacy has shifted from the use of tools toward a relationship with information, and from there to the individual's position in digital society.

When the models are compared, a similar core structure stands out despite differences in naming: technical and functional skills, cognitive and critical skills, and a social and ethical dimension. The Ng model names this triad explicitly as technical, cognitive and social-emotional dimensions (Ng, 2012), and the model of Calvani and colleagues builds a similar structure from technological, cognitive and ethical dimensions (Calvani et al., 2008). The eight-component structure of Hague and Payton presents the same core with a more detailed list of components (Hague & Payton, 2010). This overlap shows that the models can be read less as alternatives to one another than as depictions of the same phenomenon at different levels of detail.

Martin's three-stage approach differs from the others by treating digital literacy as a developing process rather than a state to be measured (Martin, 2008; Martin & Grudziecki, 2006). From the management information systems perspective, the most striking point is that the highest stage, digital transformation, describes a change in which creativity and innovation are encouraged. In other words, the model carries digital literacy from a user-level competence to a capacity that can be related to organizational innovation and technology management processes. The same model also notes that this stage is not required of every user (Martin & Grudziecki, 2006); organizations therefore need to decide deliberately which level they expect from which employees.

In education, the literature stresses two points. First, digital literacy is said to contribute to students' critical thinking, access to reliable information and conscious use; second, teachers' digital competence is regarded as a precondition for students' development (Timur et al., 2014). Krumsvik's view that skills should first be acquired by educators (Krumsvik, 2011) and the start of training for academic staff in Türkiye (YÖK, 2019) are consistent with this emphasis. Teacher competence can thus be seen as the classroom-level counterpart of digital transformation.

Most research on teachers focuses on determining the level of digital literacy. This orientation has produced a rich descriptive body of knowledge on differences by variables such as gender, age, seniority, school type, educational background and personal device ownership (Kaya-Özgül et al., 2023). By contrast, studies that address the relationship between the level of digital literacy and outcomes such as teachers' innovative behavior, entrepreneurial tendencies or organizational transformation processes remain limited within the reviewed literature. A study conducted by the author with private school teachers and currently in press reports that digital literacy plays an indirect rather than direct role in the relationship between talent management and innovative behavior and individual entrepreneurship capacities (Temel & Gündüzyeli, in press). This suggests that the concept has been examined more as a level to be measured and less as a source of other capacities. Martin's digital transformation stage offers a suitable theoretical basis for filling this gap.

Finally, the discussion of sub-disciplines points to the blurriness of conceptual boundaries. It is noted that it is difficult to draw a clear distinction between computer, library, internet, information, media, electronic information and digital information literacy (Koltay, 2011). This uncertainty brings with it the possibility that, in scale adaptation and development studies (Hamutoğlu et al., 2017; Üstündağ et al., 2017), measurements bearing the same name may cover different content. It is therefore important to state explicitly which definition and model is adopted in comparisons across studies.

9. Limitations

This chapter is not a systematic review; sources were selected around the definition, levels, skills and models of the concept rather than through a particular database search with defined criteria. It therefore cannot be claimed to represent the whole literature, and some relevant studies may have remained outside its scope.

The review is dominated by Turkish-language sources and samples of teachers or pre-service teachers. The generalizations in the chapter thus have limited validity for other occupational groups, institution types and countries. In addition, some of the sources are unpublished postgraduate theses rather than peer-reviewed journal articles; the findings of these studies have not been through an independent review process.

Finally, it should be borne in mind that, because digital technologies change rapidly, definitions, platforms and skill frameworks may quickly become outdated, and that the chapter contains no empirical test.

10. Recommendations

10.1. Recommendations for Practice

Teacher education and in-service programs should not leave digital literacy at the level of tool use. Martin's three-stage structure (Martin, 2008; Martin & Grudziecki, 2006) can guide program design: basic competence should be ensured first, the use of this competence in real teaching and work situations should then be supported, and creative and innovative practices should be encouraged among suitable individuals and groups.

Schools and other educational institutions should plan their digital transformation strategies together with the development of employees' digital literacy. Using models that address the technical, cognitive and social-emotional dimensions together (Ng, 2012) in needs analysis can reveal the shortcomings of a transformation approach based only on hardware and software investment.

At the policy level, considering that some countries have added digital literacy content to their curricula (The Royal Society, 2012) and that pilot practices were started in Türkiye (YÖK, 2019), it would be useful to establish evaluation mechanisms to monitor the results of these initiatives.

10.2. Recommendations for Research

Future studies are recommended to conduct systematic reviews based on defined criteria and to include literature in other languages.

There is a need for quantitative, qualitative and mixed-method studies that test the relationship of digital literacy with outcomes such as innovative behavior, individual entrepreneurship and participation in organizational digital transformation. In such studies, managers and employees in different sectors should be included in the sample alongside teachers, and state and private institutions should be compared. Longitudinal designs are particularly suitable for monitoring the developmental stages of digital literacy and the outcomes of these stages.

Finally, because of the blurriness of conceptual boundaries, studies are recommended to state clearly which definition and model they rely on, to support scale selection with theoretical justification and to discuss their relationship with sub-disciplines.

11. Conclusion

This chapter has reviewed digital literacy in terms of its definitions, relationship with education, developmental levels, component skills, theoretical models and sub-disciplines. Definitions were found to expand from technical usage skills toward cognitive, ethical and social dimensions, and different models were found to share a similar core structure despite differences in naming. Research on teachers, in turn, relies largely on determining levels.

The highest stage of digital literacy, which is associated with creativity and innovation, stands out as the strongest theoretical bridge linking the concept to the fields of digital transformation and technology and innovation management. Empirically testing this bridge would both close a gap in the literature and help educational institutions and other organizations manage digital transformation with attention to its human dimension.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

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CONCLUSION

We opened the Introduction with a question: how many people are sitting at the table today when a manager makes a decision? The eleven chapters of this book approached that question from different angles. In this final section, we bring together their shared messages and discuss the research agenda that lies ahead for the field.

Technology does not create value on its own. This may be the strongest message the book carries. Authors working on different topics and with different methods reached the same conclusion. The value of digital twins depends on how well their capabilities fit the requirements of decision tasks (Chapter 2). Greater AI capability does not automatically translate into greater organizational value (Chapter 3). Successful change in the age of AI is not measured by being the organization that uses the most technology (Chapter 5). Users' openness to innovation is shaped less by technical superiority than by perceived functional and emotional value (Chapter 7). In programmatic advertising, the goal is not the highest level of personalization that is technically possible but a balance between effectiveness and users' rights (Chapter 9). In short, value lies less in the technology itself than in the relationship it forms with tasks, people and organizations.

People remain at the center, but their role is changing. None of the chapters foresees a future in which humans are removed from the system. What changes is the role they play. The user is no longer simply someone who requests information. Users write prompts, evaluate outputs, correct them and take part in producing organizational knowledge (Chapters 1 and 3). In innovation, it is still people who frame the problem, interpret the context and make ethical judgments (Chapter 6). In public administration, the definition of merit is widening to include the ability to work effectively and critically with digital systems (Chapter 8). Digital literacy is following the same path. It is no longer seen merely as the ability to operate devices, and at its highest stage it becomes a capacity linked to creativity and innovation (Chapter 11). As a result, the discussion of human capital in the age of AI is shifting from "which jobs will machines do?" to "what competencies will people need to work alongside machines?"

Established theories are not being discarded; they are being extended. AI is often presented as a rupture that changes everything. The findings in this book paint a more cautious picture. Chapter 5 argues that it is too early to declare that AI has created an entirely new paradigm in change management, although it does call for a substantial paradigm extension. Chapter 8 shows that digitalization reconfigures bureaucracy rather than eliminating it. Chapter 3 treats human–AI collaboration as a continuation of human-centered design, not a replacement for it. This shared stance offers a useful caution for MIS researchers. Rather than abandoning older theories to make sense of new technology, it is more productive to ask which of their assumptions still hold and which need rethinking.

Governance is part of the system, not an add-on. Transparency, accountability, data quality, security and privacy come up in almost every chapter. In cloud computing, security complexity grows as new technologies are added (Chapter 4). In data lakes, neglecting governance and metadata management leaves the data unusable (Chapter 10). As AI agents become more autonomous, responsibility becomes spread across algorithmic recommendations, human decisions and organizational rules (Chapter 3). Meaningful human oversight therefore requires more than keeping a human "in the loop" in name only. It requires sufficient information, authority and capacity to intervene. This kind of governance should also be treated as a capability that lasts throughout the system's life cycle rather than as a one-time arrangement (Chapter 5).

Alongside these shared messages, the limitations and gaps the chapters identify also deserve attention. First, many of the conceptual models proposed in the book have not yet been tested empirically. The digital twin value-creation model, the Double-Loop AI Change Governance Model, the Human–GenAI Innovation Co-Creation Framework and the ÇAM framework all await testing through large-sample quantitative research. Concepts such as decision support capability, calibrated reliance and digital competence as merit offer fertile ground for scale development studies. Existing measures need the same care. As Chapter 11 shows, scales that carry the name digital literacy may

cover quite different content, so studies should state clearly which definition and model they adopt. Second, the empirical studies in the book rely on cross-sectional or single-context designs. Longitudinal and comparative research is needed to understand how this transformation unfolds over time. Third, the bibliometric findings show that the social sciences and management remain underrepresented in this literature, and that Turkey's contribution is still limited. For MIS researchers this is a shortcoming, but it is also a real opportunity.

The book also has implications for practice and education. For managers, the key message is that AI investments should be treated not as technology acquisition but as a redesign of task, decision and responsibility architectures. For public managers, digital transformation needs to be considered together with legislation, organizational culture and the discretion of middle-level managers. For MIS education, a new set of competencies is taking shape: prompt literacy, AI literacy, knowledge of data governance and the ability to approach algorithmic outputs critically. Built on a broader digital literacy that combines technical, cognitive and social-ethical skills (Chapter 11), these competencies do not replace technical knowledge. They complement it.

Let us return to the question we asked in the Introduction. How many people are sitting at the table today when a manager makes a decision? This book's answer is that the number matters less than the arrangement. Who proposes what, who decides and who is responsible for the outcome matter as much as who is sitting at the table. In the age of AI, the task of Management Information Systems is to design, understand and govern that arrangement. We hope this book will be a small but solid step in that direction.

Management Information Systems

Redefining Management in the Digital Age

Digital transformation, artificial intelligence, and data-driven technologies are reshaping the operations, decision-making processes, and management approaches of contemporary organizations. This book examines these transformations from a Management Information Systems perspective, adopting an interdisciplinary approach to their technological, organizational, managerial, and human dimensions. The chapters comprehensively address AI-driven organizational change, human–AI collaboration, generative AI in innovation management, big data architectures, cybersecurity in cloud computing, digital twin technologies, prompt engineering in knowledge management, programmatic advertising, technological innovativeness, and digitalization in public administration. Integrating theoretical perspectives, empirical findings, and conceptual models, the book explores how technological capabilities are transformed into organizational value. By providing a holistic examination of the opportunities and managerial challenges of the digital age, this volume serves as a comprehensive academic resource for researchers, scholars, students, and practitioners.

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