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The Role of Artificial Intelligence in Digital Maturity Models: A Bibliometric Analysis (2015–2024)

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ABSTRACT

This study investigates the role of Artificial Intelligence (AI) in advancing Digital Maturity Models (DMMs) to support digital transformation across various sectors. Although AI technologies have been widely adopted, few studies have explicitly examined how AI influences the dimensions of digital maturity or mapped the evolving research landscape on this subject. To address this gap, a bibliometric analysis was conducted using 430 journal articles published between 2015 and 2024, sourced from the Scopus database. Quantitative methods were employed using R Studio and the Bibliometrix package to analyze publication trends, keyword co-occurrences, and international research collaborations. The findings reveal a notable increase in AI-related DMM publications since 2022, with key themes including technological innovation, strategic transformation, and socio-organizational adaptation. This study contributes to the existing body of knowledge by offering a systematic overview of research developments, highlighting critical gaps, and laying the groundwork for adaptive AI maturity models. Its novelty lies in applying bibliometric techniques to uncover thematic structures that can inform future research agendas and policy directions in digital transformation.

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1. Introduction

Digital maturity and artificial intelligence (AI) are two fundamental concepts that underpin the digital transformation process across sectors. In the context of accelerating global technological change, understanding the relationship between an organization's level of digital maturity and its implementation of AI is increasingly critical for enhancing operational efficiency, competitiveness, and innovation (Androniceanu, 2024). This study aims to analyze publication trends related to AI applications within Digital Maturity Models (DMMs) using a bibliometric approach, with the objective of mapping research development and evaluating existing scholarly contributions.

AI plays a pivotal role in enabling the implementation of DMMs by assessing digital capabilities, identifying areas for improvement, and supporting more structured digital transformation planning (Brătucu et al., 2024; Schuster et al., 2021). Its integration into DMMs allows organizations to manage digital transformation more systematically, aligning technological change with strategic objectives and enhancing overall business value (Fukas, 2022).

The application of AI in DMMs offers various advantages, including improved decision-making accuracy, greater operational efficiency, and better alignment between business strategies and digital technologies (Bogoviz et al., 2021). Furthermore, AI-enabled maturity models assist organizations in deploying their technological assets more effectively, identifying capability gaps, and designing targeted development strategies (Fukas et al., 2023; Sonntag et al., 2024).

As a key driver of digital transformation, AI also facilitates advanced data analysis, automates routine tasks, and supports data-driven decision-making (Mansuri & Patel, 2022). It enables organizations to respond more swiftly to market shifts, enhance productivity, and deliver more personalized customer experiences through tailored product and service recommendations (Singh & Kaur, 2020). These capabilities position AI as a strategic asset in navigating increasingly competitive and dynamic industry environments.

Despite a growing body of research on AI integration in DMMs, several critical gaps remain. First, there is a lack of comprehensive mapping of publication trends on this topic. Second, the existing literature is fragmented, making it difficult to discern dominant patterns, key opportunities, and persistent challenges. Third, the specific contributions of AI technologies, such as machine learning and natural language processing, to different dimensions of DMMs are yet to be thoroughly examined.

To address these gaps, this study adopts a bibliometric approach. This method is well-suited for identifying dominant research themes, topic clusters, and evolving collaborative networks in the intersection of AI and digital maturity. The findings are expected to offer a systematic overview of academic developments in the field and provide a foundation for future research directions.

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2. Literature Review

2.1. Definition and Evolution of Digital Maturity Models

The Digital Maturity Model (DMM) is a strategic instrument designed not only to measure an organization's level of digitalization but also to serve as a guide for progressing toward more advanced stages of digital maturity (Thordsen & Bick, 2023). This model assesses multiple dimensions of an organization's digital capabilities, namely, technology, strategy, processes, and organizational culture, in order to identify the current digital status and areas requiring improvement (Sándor & Gubán, 2021). Despite its growing adoption, the effective implementation of DMMs continues to face challenges, particularly in adapting these models to sector-specific requirements and the fast pace of technological change.

The concept of digital maturity has evolved rapidly over the past few decades, largely driven by the increasing urgency of digital transformation across industries (Guerrero et al., 2023). Initially, DMMs were developed for specific sectors such as manufacturing, software development, and public administration (Reyes et al., 2022). As demand grew for more versatile frameworks, researchers and practitioners began developing models that are adaptable to a wider range of sectors. These include tailored DMMs for small and medium-sized enterprises (SMEs), service-oriented businesses, and the construction industry (Han et al., 2024). Although such contextualization enhances the applicability of DMMs, a critical gap remains in assessing their overall effectiveness and adaptability to future challenges in digital transformation.

2.2. Role of Artificial Intelligence in Digital Transformation

Artificial Intelligence (AI) plays a significant role in enhancing operational efficiency and optimizing business processes (Salgado-Reyes et al., 2024). Through the automation of repetitive tasks, AI enables organizations to streamline workflows, reduce operational costs, and increase productivity (Chakir et al., 2024). In the energy sector, particularly in power grid management, AI technologies such as computer vision and natural language processing facilitate data-driven decision-making, which can improve both efficiency and system reliability (Li et al., 2024). However, the implementation of AI in manufacturing-based small and medium-sized enterprises (SMEs) often encounters barriers, including high initial investment costs and limited workforce readiness (Peretz-Andersson et al., 2024). These factors must be addressed to ensure the effective integration of AI in such contexts.

Beyond internal operations, AI also enhances customer engagement through personalized services (Bui & Nguyen, 2023). By leveraging data analytics, businesses can gain deeper insights into consumer behavior and deliver more tailored experiences, including the use of chatbots to expedite information delivery in public sector services (Pislaru et al., 2024). Nevertheless, concerns over data privacy and the transparency of AI algorithms remain prominent. Striking a balance between technological advancement and the protection of individual privacy rights is essential to sustaining public trust in AI applications.

Moreover, AI contributes to strategic decision-making and catalyzes innovation (Svetlana et al., 2022). Its capacity for large-scale data analysis enables organizations to refine their strategic responses to market dynamics and develop new products and services that align with emerging demands (Pooja et al., 2024). At the same time, regulatory complexities and the risk of algorithmic bias require careful management to ensure that AI is applied ethically and responsibly. When implemented strategically and conscientiously, AI has the potential to drive digital transformation while upholding efficiency, innovation, and social accountability.

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2.3. Challenges in AI Implementation for Digital Maturity Models

The integration of Artificial Intelligence (AI) into Digital Maturity Models (DMMs) presents a range of technical and managerial challenges. One of the primary obstacles is ensuring the compatibility of AI systems with existing information technology (IT) infrastructures, which frequently necessitates substantial restructuring of digital architectures and operational processes (Echeberria, 2022). Moreover, the absence of standardized procedures for AI implementation often hampers coordination between AI developers and functional departments, increasing the risk of miscommunication and operational inefficiencies (Müller et al., 2023). These technical issues are further intensified by the growing demand for explainable artificial intelligence (XAI), which aims to ensure transparency, interpretability, and accountability in AI-driven decision-making processes (Chiu & Yang, 2024). Although conceptual frameworks such as Gartner's AI Maturity Model offer strategic orientation, they often fall short in providing detailed, actionable guidance for implementation across diverse industry contexts.

In addition to technical constraints, organizations must navigate complex ethical, privacy, and regulatory challenges. AI technologies are expected to comply with ethical norms and data protection laws, which differ significantly across jurisdictions (Schuster et al., 2021). The dynamic nature of both regulatory landscapes and technological innovation further complicates compliance efforts (Schuster & Waidelich, 2022). Public sector institutions, in particular, encounter additional hurdles due to strict regulatory requirements and intricate procurement procedures, which can delay or hinder the adoption of AI systems (Mergel et al., 2023). While international frameworks such as the European Union's AI Ethics Guidelines and Singapore's AI Governance Framework provide valuable reference points, their applicability remains limited when adapted to varied organizational and national contexts.

To address these multifaceted challenges, organizations must adopt an integrative and balanced strategy, one that considers not only technical feasibility and operational readiness but also regulatory alignment and ethical responsibility. By doing so, they can more effectively harness the potential of AI to drive digital transformation and enhance their competitive position in an increasingly data-driven global economy.

3. Research Methodology

3.1. Research Type

This study employs a quantitative research methodology, specifically using bibliometric analysis to systematically examine patterns, trends, and thematic developments related to the application of Artificial Intelligence (AI) in Digital Maturity Models (DMMs). Quantitative research is characterized by its formal, objective, and structured approach to data collection and analysis (Barkman, 2016; Lam & Chan, 2010). It is widely valued for its capacity to generate findings that are objective, replicable, and generalizable, attributes that are essential for informing theoretical development, practical application, and policy-making across disciplines (Claydon, 2015). The rigor of its methodology enhances both the validity and reliability of the research outcomes.

3.2. Research Data Source

This study relies exclusively on the Scopus database as the source of bibliometric data, given its extensive coverage of high-quality academic journals and consistent standards for article validation. Compared to other indexing services, Scopus includes a broader range of publication formats, such as conference proceedings and academic books, which are often

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underrepresented in databases like Web of Science (Meden & Cvek, 2021). Previous studies have indicated that Scopus tends to yield higher citation counts, reinforcing its utility for bibliometric research and comprehensive scholarly evaluation (Lasda Bergman, 2012).

3.3. Data Collection Techniques

This study employs bibliometric analysis to examine scholarly publications addressing the role of Artificial Intelligence (AI) in the context of Digital Maturity Models (DMMs) over the period 2014 to 2024. The dataset was sourced from the Scopus database, selected for its comprehensive coverage of peer-reviewed literature and its rigorous standards for publication quality (Baas et al., 2020; Ballew, 2009). The analysis focused exclusively on journal articles published in English, excluding other document types such as conference proceedings, book chapters, and review articles.

The literature search was conducted using the following query string:
(TITLE-ABS-KEY("Digital Maturity" OR "Maturity") AND TITLE-ABS-KEY("Artificial Intelligence")) AND PUBYEAR > 2014 AND PUBYEAR < 2025 AND (LIMIT-TO(LANGUAGE, "English")) AND (LIMIT-TO(SRCTYPE, "j")) AND (LIMIT-TO(DOCTYPE, "ar"))

This search yielded an initial sample of 430 articles. A systematic data-cleaning procedure was subsequently implemented to enhance the quality and relevance of the dataset. This process involved the removal of duplicate entries and the exclusion of publications that, upon abstract screening, did not explicitly address the application of AI within the framework of digital maturity models.

In addition, a keyword standardization procedure was applied to ensure terminological consistency across the dataset. For instance, terms such as "AI" were uniformly recoded as "Artificial Intelligence," and references to "Maturity Model" were standardized to "Digital Maturity Model" where appropriate. These refinements were essential for improving the validity and reliability of the bibliometric analysis.

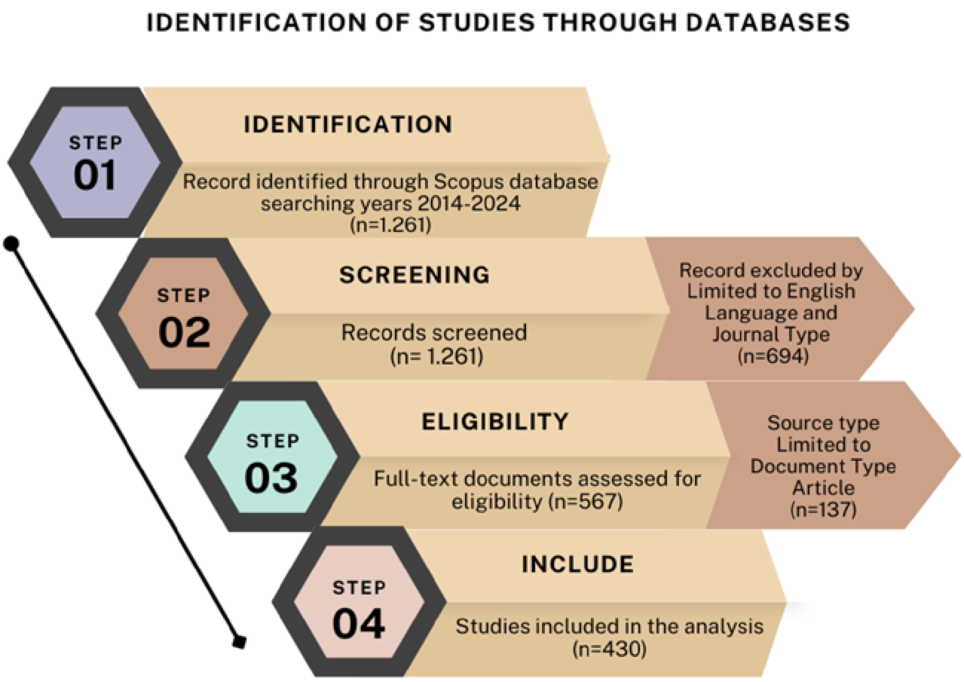

Figure 1. Prisma Chart
Source: Data Analysis Process

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3.4. Data Analysis Techniques

R Studio was utilized as the primary platform for data analysis due to its robust capabilities in statistical computation and data visualization. As an open-source software with strong community support, R Studio is widely recognized for its utility in advanced-level research involving quantitative analysis (Kumar & Tyagi, 2024).

The thematic analysis in this study was conducted through a bibliometric approach, employing several analytical functions available within R. Core themes and research trends were identified using keyword analysis and network mapping, facilitated by R packages such as *bibliometrix* and *tm*. Thematic classification was carried out using the co-word analysis technique, which clusters terms that frequently co-occur within related publications.

In addition, conceptual mapping and network visualization were employed to uncover the interrelationships among emerging topics associated with AI-driven Digital Maturity Models. These techniques enabled a structured examination of the research landscape and provided insights into how thematic developments are interconnected across the body of literature.

4. Results and Discussion

4.1. Mapping Research Productivity and International Partnerships

The number of publications and the extent of international research collaborations serve as key indicators in assessing the development and dynamics of a particular academic field. Publication volume reflects the level of scholarly productivity and the degree of interest within the scientific community regarding a specific research area. In parallel, collaboration networks illustrate the patterns of cooperation among researchers, institutions, and countries, thereby revealing how knowledge is shared and innovation disseminated on a global scale. Analyzing these two indicators enables the identification of prevailing research trends, potential synergies among stakeholders, and future opportunities for advancing contributions within the field.

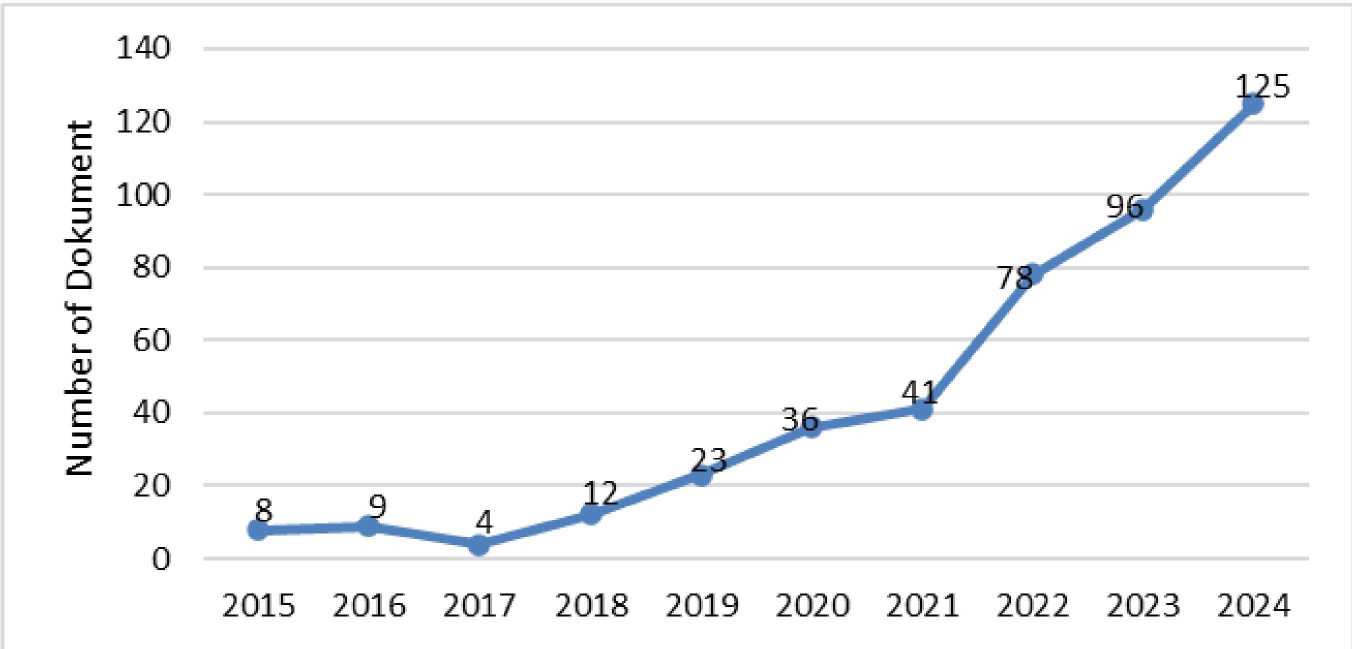

Figure 2. Research Trends by Year
Source: Scopus Database

Figure 2 illustrates the growth trajectory of scholarly publications focusing on Artificial Intelligence (AI) in the context of digital transformation from 2015 to 2024. A notable surge in

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publication activity has occurred since 2021, coinciding with the initial wave of technology adoption in areas such as smart metering and the development of Digital Maturity Models (DMMs). This upward trend underscores the growing academic interest in integrating AI into digital maturity assessment frameworks across both public and private sectors.

The increase in research output after 2021 can be attributed to the accelerated global push for digital transformation in the aftermath of the COVID-19 pandemic. This shift has prompted organizations to adopt data-driven strategies and AI technologies more rapidly (Ong & Lee, 2024). These findings reinforce the notion that AI is not merely a technological advancement but also a strategic pillar in the design of more adaptive, automated, and prescriptive models for assessing digital maturity.

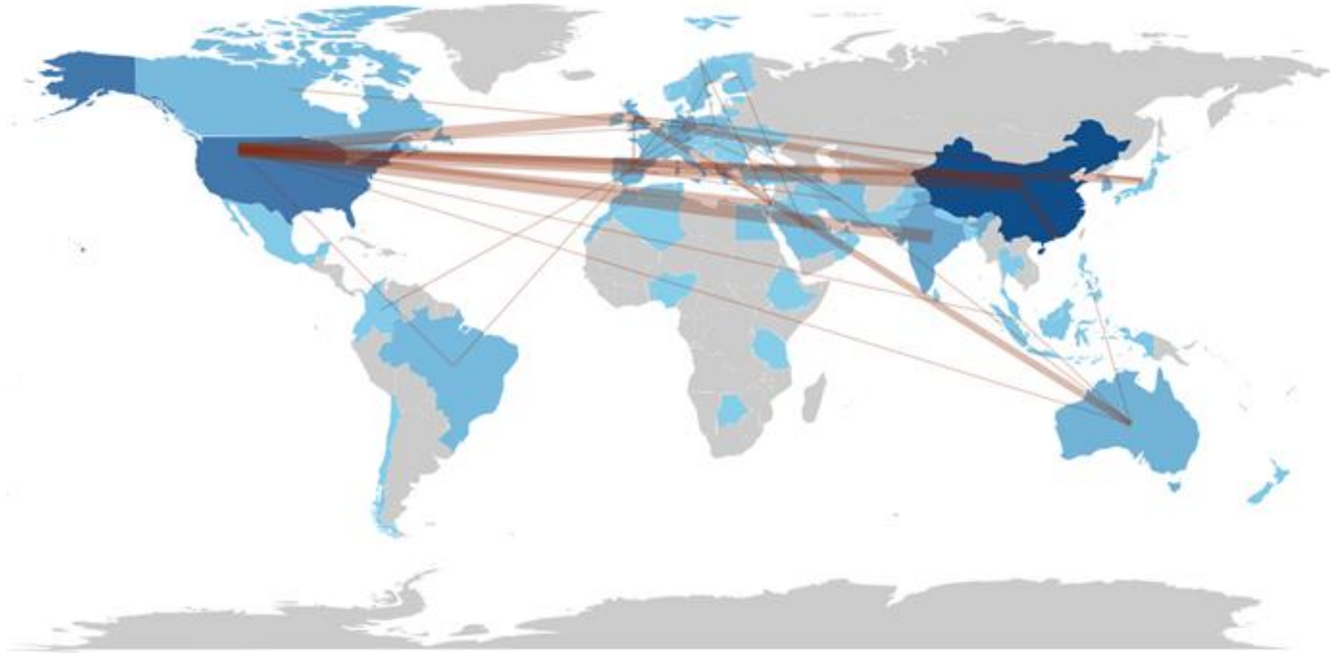

Figure 3. Collaboration Map
Source: R Studio

Figure 3 displays a global map of research collaborations among scholars investigating the intersection of Artificial Intelligence and Digital Maturity Models. The data reveal that leading collaborative activities originate from institutions in the United States, China, and Australia, each serving as a hub for generating and disseminating knowledge in this domain. This pattern highlights the central role of transnational academic partnerships in advancing interdisciplinary approaches to AI-based digital maturity frameworks. Furthermore, the strength and breadth of these collaborations demonstrate that the discourse on digital maturity, especially when supported by intelligent technologies, has become a truly global concern, necessitating cross-border knowledge exchange and collective innovation.

4.2. Trends and Issues of Artificial Intelligence in Digital Maturity Models

Research on trends and emerging issues provides an in-depth examination of the current dynamics and challenges associated with the integration of Artificial Intelligence (AI) in Digital Maturity Models (DMMs). The objective is to identify prevailing patterns and shifts in scholarly focus. Within the framework of biblioshiny analysis, this process involves tracking the latest

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developments in scientific publications, identifying emerging technologies and strategic approaches, and assessing the barriers and opportunities that accompany the evolution of AI-related research. By understanding these trends, researchers can pinpoint areas of accelerated growth and address critical challenges that influence both theoretical advancement and the practical implementation of AI-based DMMs.

Figure 4. Topic Emergence of Artificial Intelligence in Digital Maturity Models
Source: R Studio

Figure 4 illustrates the dominant thematic focus in research addressing the application of AI within DMMs. Prominent terms such as *deep learning*, *maturity model*, *artificial intelligence*, *industry 4.0*, and *big data* highlight the core areas of scholarly interest. The appearance of keywords such as *decision support*, *classification*, and *digital transformation* further indicates that much of the existing literature positions AI as a strategic tool for decision-making and the optimization of digital processes (Funda & Francke, 2024; Mannava, 2024). These findings suggest a growing alignment between AI technologies and organizational strategies for digital transformation.

Table 1. Topic Trends

Topic	Frequency	Year_Q1	Year_Med	Year_Q3
big data	19	2020	2021	2023
neural networks	5	2021	2021	2022
machine learning	54	2021	2022	2023
maturity model	20	2020	2022	2024
industry 4.0	19	2020	2022	2022
artificial intelligence	145	2022	2023	2024
deep learning	27	2023	2023	2024
image processing	7	2022	2023	2024
artificial intelligence (AI)	16	2021	2024	2024
ChatGPT	8	2023	2024	2024

Source: R Studio

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Table 1 presents the frequency and chronological distribution of key topics in the literature concerning the integration of AI into DMMs. Artificial intelligence appears as the most frequently discussed theme, with 145 publications and a consistent upward trend from 2022, peaking in the third quarter of 2024. This reflects a heightened sense of urgency among scholars and practitioners to leverage AI for systematic digital transformation.

Additionally, terms such as *machine learning*, *deep learning*, and *big data* demonstrate strong temporal consistency and thematic relevance, indicating their foundational role in supporting DMMs through automation, predictive analytics, and data-driven strategies. The appearance of *ChatGPT* and *artificial intelligence (AI)* as separate entries beginning in 2023 further reflects the research community's growing interest in large language models (LLMs) and generative AI systems as components of organizational digital architecture (Sundberg & Holmström, 2024).

The inclusion of quartile-based temporal markers (Year_Q1, Year_Med, and Year_Q3) offers a longitudinal perspective on topic emergence and maturation. Most themes began to surface between 2020 and 2021, expanded notably between 2022 and 2023, and reached heightened scholarly attention by 2024. This progression highlights a shift from conceptual exploration toward more practical, measurable, and strategic applications of AI within the framework of digital maturity.

Thus, the findings in this section go beyond presenting statistical data, they underscore the centrality of AI integration as a core axis in the advancement of digital maturity models, with implications for both public sector innovation and private sector competitiveness in an increasingly data-driven and automated landscape.

4.3. Conceptual Structure Map: Topic Mapping

Topic mapping is a methodological approach in scientific analysis that seeks to identify, visualize, and interpret the relationships and structural patterns present within the research literature. This technique enables scholars to examine the interconnections among research themes, detect prevailing trends, and uncover clusters of topics that frequently co-occur in academic publications.

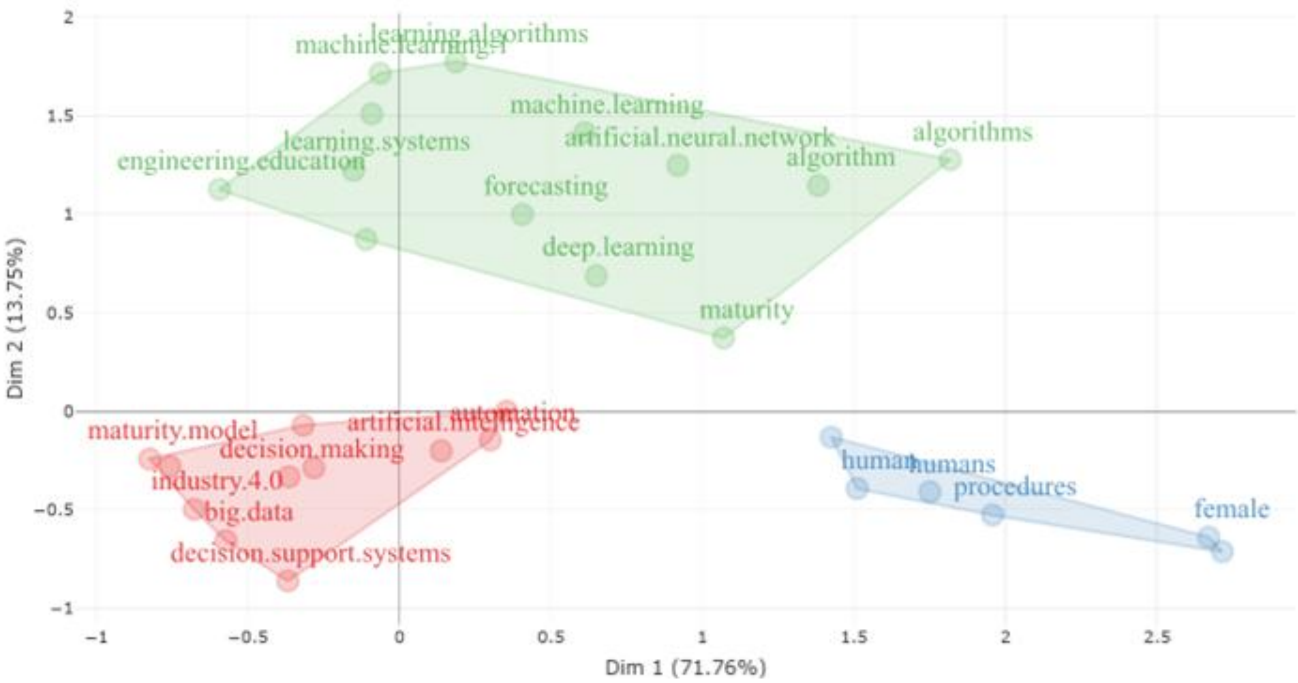

Figure 5. The Conceptual Structure Map
Source: R Studio

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Figure 5 illustrates the conceptual structure of research focusing on Artificial Intelligence (AI) within the framework of Digital Maturity Models (DMMs). The visualized data reveal three primary thematic clusters. The green cluster centers on technical aspects and algorithmic development, encompassing keywords such as *machine learning*, *deep learning*, and *artificial neural networks*. The red cluster includes themes oriented toward applied practices, such as *decision support systems*, *industry 4.0*, and *maturity models*. The blue cluster represents topics related to social and organizational dimensions, including terms like *humans*, *procedures*, and *female*.

The spatial arrangement of these clusters demonstrates the multidisciplinary nature of current research on AI integration in DMMs. It reflects a convergence of technical innovation, strategic deployment, and socio-organizational dynamics. Notably, the positioning of the strategic application cluster between the technical and social domains suggests an integrative effort to bridge computational development with human-centered implementation challenges.

This conceptual mapping provides valuable insights into how various research threads interrelate and evolve. It also underscores that the scholarly ecosystem surrounding AI-based digital maturity models remains dynamic. It is progressively moving toward a more holistic, cross-dimensional framework that integrates technological, strategic, and social perspectives.

4.4. Evolution of Artificial Intelligence Topics in Digital Maturity Models

The evolutionary mapping of research topics provides a visual depiction of how scholarly attention and thematic focus regarding Artificial Intelligence (AI) in Digital Maturity Models (DMMs) have shifted over time. This progression reflects broader transformations in technological trends, policy orientations, regulatory frameworks, digital governance mechanisms, and strategic priorities related to the implementation of AI in assessing and advancing digital maturity.

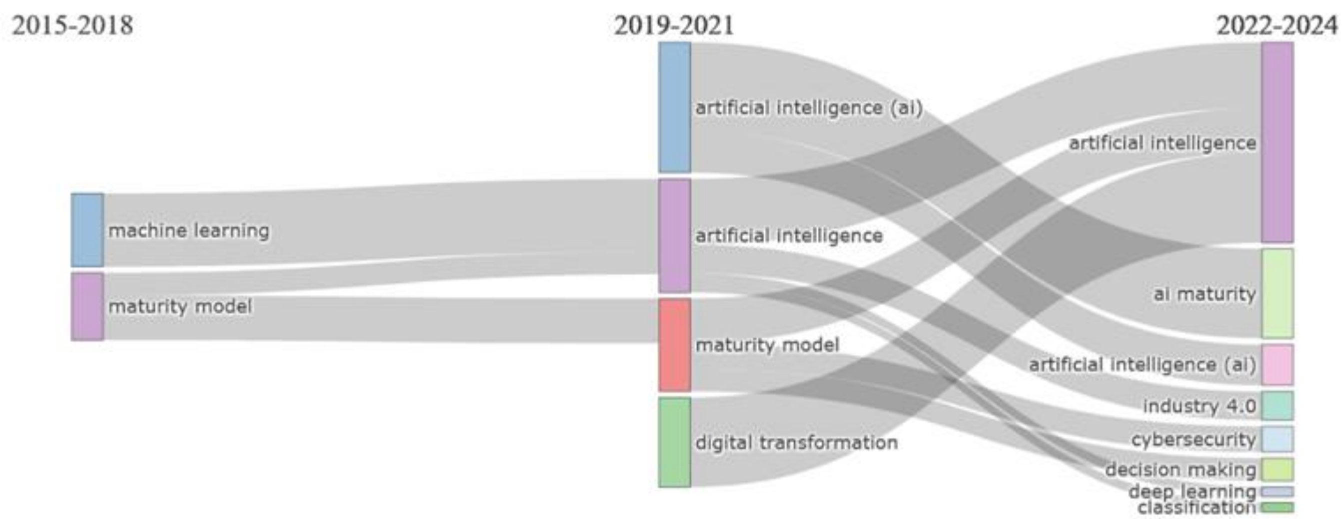

Figure 6. The Evolution of Artificial Intelligence Topics in Digital Maturity Models
Source: R Studio

Figure 6 presents the chronological development of major research themes concerning the intersection of AI and DMMs across three distinct periods: 2015–2018, 2019–2021, and 2022–2024. During the initial phase (2015–2018), scholarly discourse was primarily concentrated on

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machine learning and *maturity models*, indicating an early focus on the technical foundations of digital capability assessment and the construction of evaluative frameworks.

In the second phase (2019–2021), the scope of research expanded significantly with the introduction of broader concepts such as *artificial intelligence* (*AI*) and *digital transformation*. This shift reflects a transition from narrowly technical inquiries to integrative discussions on the role of AI in facilitating organization-wide transformation. While maturity models remained a central theme, they increasingly served as conceptual bridges between technological development and strategic organizational implementation.

In the most recent phase (2022–2024), the thematic landscape has become more diversified. New topics such as *AI maturity*, *cybersecurity*, *deep learning*, *classification*, and *decision making* have emerged. The prominence of *AI maturity* indicates a growing interest in developing evaluative frameworks that focus on an organization's preparedness and effectiveness in adopting AI for operational and governance purposes (Roszelan & Shahrom, 2025). Concurrently, the appearance of *cybersecurity* and *decision making* as key themes points to a deepening recognition of AI not merely as a technical solution, but as a strategic asset in risk management and organizational planning.

Taken together, this evolution reflects an increasingly complex and interdisciplinary body of research. It signifies a movement from early-stage technological exploration toward the systemic application of AI in digitally mature organizations. Moreover, it highlights the importance of adopting a holistic and adaptive approach in the design and implementation of AI-integrated DMMs, particularly in light of emerging ethical, regulatory, and operational considerations.

4.5. The Role of Artificial Intelligence in Improving Digital Maturity Models

Artificial Intelligence (AI) has emerged as a critical enabler in enhancing organizational digital maturity, particularly through its capabilities in automation, predictive analytics, and data-driven decision-making. Within the framework of Digital Maturity Models (DMMs), however, the role of AI cannot be fully understood without reference to the underlying theoretical foundations, including the Technology-Organization-Environment (TOE) framework, Dynamic Capabilities Theory, and the AI Maturity Models approach. The findings of this study suggest that the integration of AI into DMMs reflects a conceptual shift, from viewing technology merely as a supportive tool to recognizing it as a strategic asset that actively shapes the trajectory of digital transformation.

The conceptual mapping presented in **Figure 5** illustrates three primary clusters: technical algorithmic, strategic organizational, and socio-marginal. The technical cluster, represented by themes such as *machine learning* and *deep learning*, demonstrates advancements in the development of AI-based systems aimed at increasing operational efficiency (Uriarte-Gallastegi et al., 2023). The strategic cluster, which includes *decision support systems*, *industry 4.0*, and *maturity models*, highlights AI's role not just as a technological enhancement but as a foundational element in the formulation of policy and organizational strategy (Gupta et al., 2023; Muala et al., 2024). The social cluster, though relatively peripheral, reflects ongoing challenges in embedding human and organizational factors within digital transformation initiatives, an issue emphasized within socio-technical systems theory.

Furthermore, the evolution of research topics illustrated in **Figure 6** underscores a thematic shift over time, from early focus areas such as *maturity models* and *machine learning* (2015–2018), to broader themes like *artificial intelligence* and *digital transformation* (2019–2021), and most recently, to more applied and evaluative concepts such as *AI maturity*, *cybersecurity*, and *decision*

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making (2022–2024). This progression signals the growing recognition of AI as a core architectural component of digitally mature organizations. It aligns with frameworks like the AI Maturity Model (Yablonsky, 2021), which categorize organizations according to their readiness and capacity to integrate AI technologies strategically.

These findings carry important practical implications. In the industrial sector, the adoption of AI within the DMM framework enables more precise identification of digital capability gaps and supports the development of data-informed strategies. In the public sector, the same framework can serve as a diagnostic tool for assessing institutional readiness for AI adoption, including regulatory compliance, organizational competence, and ethical considerations. From an academic perspective, this study highlights the need to examine the complex interplay between technological innovation, institutional capacity, and socio-cultural dimensions in digital transformation processes.

In this context, AI should no longer be viewed merely as an auxiliary technology, but rather as a transformative catalyst that redefines how organizations assess, design, and implement their digital strategies. Future research should deepen this understanding through the integration of established theoretical models and through empirical investigations across sectors, in order to support the sustainable and effective deployment of AI-based digital transformation initiatives.

5. Conclusion

This study contributes to the conceptual understanding of the role of Artificial Intelligence (AI) in enhancing Digital Maturity Models (DMMs) through a bibliometric lens. The findings reveal that the integration of technologies such as machine learning, deep learning, and large language models significantly supports automation, data-driven decision-making, and systematic evaluation of organizational digital readiness. These results affirm that AI functions not merely as a technical instrument but also as a strategic driver that influences governance structures and the broader digital architecture of organizations.

The primary academic contribution of this research lies in the construction of a thematic map and the illustration of conceptual evolution, both of which trace the shifting focus of scholarly inquiry toward the integration of AI within the technical, strategic, and social dimensions of DMMs. These insights provide a valuable foundation for the development of a refined conceptual framework that merges the socio-technical systems perspective with dynamic capabilities theory to explain better how organizations sustainably adapt to the complexities of AI-based digital technologies.

Nonetheless, this study is subject to several limitations. The analysis relies exclusively on data from the Scopus database and is limited to English-language journal articles. Moreover, the bibliometric approach employed is exploratory in nature and does not capture the depth of real-world implementation. Future research should aim to construct a more adaptive and context-sensitive model of AI-integrated digital maturity that is applicable across diverse sectors. Employing mixed methods, such as qualitative case studies and longitudinal designs, will enhance the empirical robustness of future work and facilitate the development of actionable models for the public sector, manufacturing industries, micro, small, and medium enterprises (MSMEs), and public service institutions.

Further research should also address ethical considerations, organizational culture, and the broader social implications of AI implementation, all of which are essential for measuring and fostering genuine digital maturity.

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7. Declaration of Conflicting Interests

The authors have declared no potential conflicts of interest regarding this article's research, authorship, and/or publication.

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