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AI and Digital Transformation Trends: A Systematic Review with Multi-Criteria Analysis

Soni Adiyono[1], **Muhammad Arifin**[2]

[1,2] Information System Department, Muria Kudus University, Gondangmanis, Central Java 59327, Indonesia

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Corresponding Author:
Author Name*:
Soni Adiyono
Email*:
soni.adiyono@umk.ac.id

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Abstract. This research investigates the integration of Artificial Intelligence (AI) and Digital Transformation (DT) as critical enablers of Industry 4.0, highlighting their combined influence in reshaping industrial processes and enhancing operational efficiency. AI technologies, including machine learning, natural language processing, and computer vision, are driving advancements in automation, real-time decision-making, and personalized services across various industries, such as manufacturing, healthcare, and logistics. DT involves the widespread adoption of digital technologies that transform business models, stakeholder interactions, and organizational structures, working synergistically with AI to foster innovation. While existing literature often examines AI and DT in isolation, this study addresses the gap by employing a Systematic Literature Review (SLR) and Multi-Criteria Analysis (MCA) methodology to evaluate research based on academic impact, practical relevance, and sectoral readiness. The analysis reveals emerging trends such as predictive analytics, autonomous systems, and smart manufacturing, with industries like healthcare and retail showing strong adoption, while real estate and legal services remain underexplored. The research examines 46,936 Scopus records and selects 32 studies for analysis. The MCA results underscore the importance of aligning academic research with industrial needs and fostering cross-sector collaboration. Ultimately, this study bridges the gap between theory and practice, offering valuable insights for policymakers, scholars, and practitioners to strengthen competitive advantage in the digital era.

Keywords: Artificial Intelligence, Digital Transformation, Industry 4.0, Predictive Analytics, Cross-Sector Collaboration.

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has fundamentally reshaped industrial processes, driving innovation, efficiency, and competitiveness across various sectors. AI technologies, such as machine learning, natural language processing, and computer vision, have enabled industries to optimize operations, enhance decision-making, and improve customer experiences[1]. Recent studies have emphasized that the convergence of AI and DT represents not only a technological transformation but also a socio-economic shift that redefines industrial competitiveness and innovation ecosystems. AI-driven analytics and automation are becoming central to operational excellence and predictive decision-making across sectors such as energy, logistics, and smart cities [2] [3]. Meanwhile, DT facilitates the integration of cyber-physical systems and Internet of Things (IoT) technologies that enable real-time data flows, connectivity, and system interoperability [4]. The synergy between AI and DT is increasingly viewed as the foundation of the transition toward Industry 5.0, characterized by human–machine collaboration, sustainability, and resilience [5]. These technological trends indicate that successful digital transformation requires not only technological adoption but also strategic alignment between digital capabilities, organizational culture, and workforce readiness.

By processing vast amounts of data at unprecedented speeds, AI has revolutionized areas such as predictive maintenance, supply chain optimization, and customer engagement [6]. As industries increasingly adopt these technologies, AI is no longer seen as a luxury but as a necessity for maintaining a competitive edge. Its integration into industrial processes is a key driver of the broader evolution toward Industry 4.0, where automation, interconnectivity, and data-driven insights redefine traditional industrial paradigms [7].
Industry 4.0 frameworks highlight how AI enables adaptive manufacturing systems, autonomous process control, and enhanced supply-chain transparency through intelligent sensing and real-time analytics [8][9]. Researchers have also identified digital twins and big data analytics as crucial components for achieving operational agility and sustainable industrial performance [9][10]. In this context, organizations that successfully integrate AI into DT strategies demonstrate greater efficiency, reduced downtime, and improved innovation capacity, positioning them as digital leaders in competitive markets.

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In parallel, the concept of Digital Transformation (DT) has gained significant attention as companies strive to adapt to rapidly changing technological landscapes. DT refers to the integration of digital technologies into all areas of a business, fundamentally changing how organizations operate and deliver value to customers [11]. Unlike incremental improvements, DT involves a holistic rethinking of business processes, organizational structures, and stakeholder engagement [12]. In industrial contexts, DT has enabled companies to streamline production, enhance flexibility, and respond more quickly to market demands. When combined with AI, DT becomes a powerful tool for enabling intelligent factories, real-time monitoring, and personalized customer experiences, making it a cornerstone for sustaining competitiveness in the digital age [13]. The convergence of AI and DT has become a central pillar of Industry 4.0, which represents the fourth industrial revolution driven by smart technologies and connected systems. This convergence unlocks unprecedented value by enabling autonomous decision-making, predictive analytics, and seamless integration across industrial ecosystems [7][1]. For example, AI-driven solutions have been widely implemented in sectors such as healthcare, logistics, and manufacturing, enabling automation, real-time decision-making, and improved customer experiences [6]. However, despite its transformative potential, the research landscape on AI and DT remains fragmented, with studies often focusing on isolated aspects rather than presenting a holistic view [12]. Understanding temporal trends in AI and DT research is crucial for identifying emerging themes, guiding future investigations, and ensuring alignment with evolving industrial demands.

Existing methodologies for synthesizing research, such as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, offer a structured approach to conducting systematic literature reviews (SLR) [14]. PRISMA is widely used across disciplines for identifying, screening, and synthesizing research trends. However, while effective in providing a broad overview, PRISMA often lacks mechanisms to evaluate the relevance of studies based on criteria such as academic impact, practical applicability, and temporal relevance. This limitation is particularly critical for fields like AI and DT, where relevance is multidimensional. For instance, a study with high academic impact may have limited practical application, while another focusing on outdated technologies may no longer align with the needs of modern industries [12][15]. Furthermore, there are few systematic approaches that address sectoral readiness and the varying technological or financial barriers faced by industries adopting AI and DT.

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This study addresses these gaps by employing a multi-criteria decision-making (MCDM) methodology integrated with a systematic literature review (SLR). This approach enables the identification of temporal trends and sectoral variations in the adoption and impact of AI and DT. Drawing on methodologies established in prior SLRs of MCDM applications in areas such as smart cities and energy policy, the present study extends these principles to assess research relevance in industrial contexts [7][12]. By focusing on temporal and cross-sectoral analyses, this study provides a roadmap for understanding how these technologies evolve and influence various industry sectors. Specifically, the integration of MCDM allows for a more nuanced evaluation based on factors such as technological readiness, sectoral impact, and research innovation, addressing critical gaps in existing literature. This study offers two key contributions to the existing body of knowledge. First, it provides a comprehensive overview of temporal trends in AI and DT research, highlighting shifts in focus, emerging themes, and areas of growing importance over time. Second, it introduces a methodological enhancement to the PRISMA framework, incorporating a multi-criteria weighting mechanism to evaluate the relevance of research. By synthesizing these insights, the study aims to bridge the gap between academic research and industrial practice, ensuring that AI and DT innovations remain aligned with the dynamic needs of industries. Ultimately, this research provides actionable insights for scholars, policymakers, and practitioners, serving as a guide for advancing the integration of AI and DT in industrial environments.

Although both AI and DT have attracted substantial academic and industrial attention, the majority of research remains fragmented, focusing on single-technology adoption or sector-specific outcomes rather than comprehensive integration models [16][17]. For example, while manufacturing studies often examine automation and predictive maintenance, service sectors tend to emphasize customer analytics and chatbot applications. This disciplinary separation limits the development of unified frameworks capable of measuring the cross-sectoral impact of AI-enabled transformation. Recent literature calls for integrative reviews that map technological convergence, assess readiness levels, and identify policy barriers across industries [17][18].

Second, it introduces a methodological enhancement to the PRISMA framework, incorporating a multi-criteria weighting mechanism to evaluate the relevance of research. By synthesizing these insights, the study aims to bridge the gap between

academic research and industrial practice, ensuring that AI and DT innovations remain aligned with the dynamic needs of industries. Specifically, this research seeks to answer two fundamental questions:

1) How have temporal trends shaped AI and digital transformation research across industries?
2) What are the critical factors influencing the relevance and impact of research in this domain?

By addressing these questions, the study provides actionable insights for scholars, policymakers, and practitioners, serving as a guide for advancing the integration of AI and DT in industrial environments. Ultimately, these findings aim to inform future research and help industries prioritize investments in technologies that offer the highest potential for impact. The primary objective of this study is to develop a comprehensive understanding of how AI and DT converge to drive innovation across various sectors, while also identifying underexplored areas and emerging opportunities. The novelty of this research lies in its combined use of Systematic Literature Review (SLR) and Multi-Criteria Analysis (MCA), offering a robust and multi-dimensional framework to evaluate research relevance, sectoral readiness, and the practical alignment of academic findings with industrial needs. This approach not only bridges existing gaps in the literature but also provides a unique lens for exploring the evolving dynamics of AI and DT in Industry 4.0.

The remainder of this paper is organized as follows. Section 2 explains the PRISMA-based search and screening procedure and details the multi-criteria analysis design. Section 3 presents the results, including temporal trends and sectoral distribution. Section 4 discusses the findings in relation to the two research questions and highlights implications. Section 5 concludes the paper and outlines limitations and future research directions.

2. METHODS

Figure 1 illustrates a phased screening procedure designed to identify relevant research articles on artificial intelligence, digital transformation, and industry trends. The process begins with an initial broad screening stage, where a comprehensive search query

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reduces the initial pool of 46,936 documents to 27,102 by filtering out irrelevant studies. Subsequent stages refine the dataset further by applying specific criteria, such as publication year, document type, and relevant keywords. Each phase progressively narrows the selection to ensure only high-quality, pertinent literature is retained. The final stage involves extracting data from the refined set of articles and performing a multi-criteria analysis to evaluate findings and identify key trends in the research landscape. This structured, step-by-step approach prioritizes relevance, enabling a focused analysis of industry-related research while ensuring meaningful insights and trends are systematically captured.

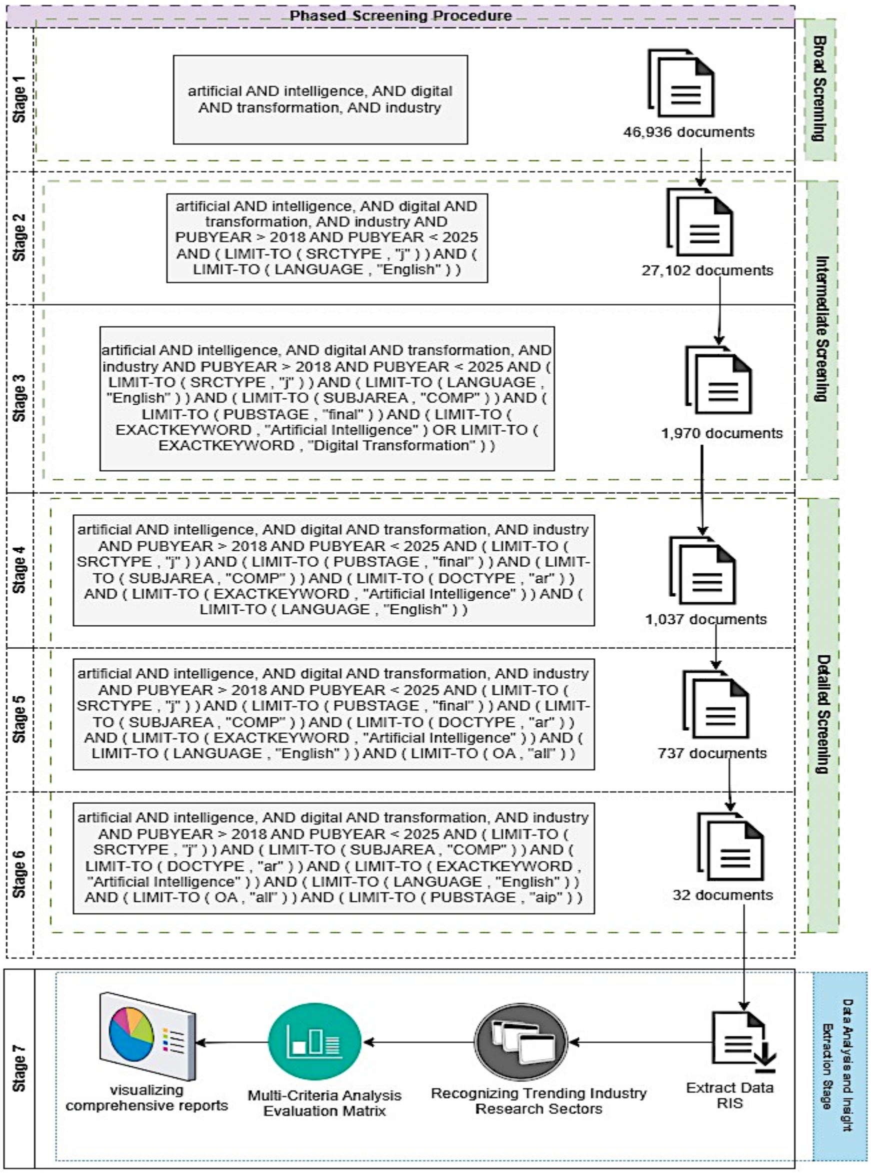

Figure. 1: Phased Screening Framework for Industry Trend Analysis

To ensure methodological transparency and reproducibility, the review procedure was designed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [19] [20] [21]. The process involved structured search strategies, inclusion–exclusion criteria, and multi-stage screening to minimize bias. Such rigor, widely adopted in management and information systems research [22] [23] [24], allows a comprehensive mapping of the literature while ensuring traceability and replicability. Coding of study metadata including research context, methodology, and domain was standardized to enable cross-comparative analysis and to enhance interpretative validity across industrial sectors.

2.1. Search Strategy

This study followed a PRISMA-guided systematic literature review procedure to ensure transparency and reproducibility. The literature search was conducted in Scopus because it provides broad coverage of peer-reviewed journals relevant to Artificial Intelligence (AI), Digital Transformation (DT), and industry applications. The search was designed to capture studies explicitly addressing AI and DT in industrial/sectoral contexts. The initial search returned 46,936 records prior to screening and refinement.

Table 1. Search strategy summary (Scopus)

Item	Description
Database	Scopus
Search Fields	TITLE-ABS-KEY
Search string (full query)	TITLE-ABS-KEY (("artificial intelligence" OR "AI") AND ("digital transformation" OR "DT") AND (industry OR industrial OR sector*))
Filters	Year: 2018–2025; Language: English; Document type: Journal article
Additional refinement	Targeted keyword refinement and publication-stage filtering applied during intermediate phases
Open Access Filter	Applied during Phase 5 to ensure full-text accessibility
Final included studies	32

2.2. Intermediate Screening

Screening was conducted in multiple phases to progressively refine the evidence base. In the initial phase, a broad keyword search (AI, digital transformation, and industry) produced 46,936 records. Subsequent screening phases applied restrictions to focus the dataset on recent and relevant peer-reviewed journal literature: publication years 2018–2025 and English-language journal articles reduced the dataset to 27,102 records. Additional refinement using targeted keywords, publication-stage filters, and document-type constraints reduced the results to 1,970 and then 1,037 records. Open-access filtering was applied in Phase 5 to ensure full-text accessibility during detailed eligibility assessment, reducing the dataset to 737 records. The final eligibility screening retained 32 studies for analysis. Inclusion criteria were: (i) explicit discussion of AI in relation to DT, (ii) relevance to industry/sector context (application, adoption, governance, or organizational transformation), (iii) peer-reviewed journal article, and (iv) publication within 2018–2025. Exclusion criteria included: non-English papers, non-journal documents (e.g., conference papers, editorials), duplicates, and studies not addressing AI–DT convergence in an industrial or sectoral context.

2.3. Open-Access Filtering (Constraint and Limitation)

Open-access (OA) filtering was used as a practical constraint to ensure the research team could access and assess full texts consistently during eligibility screening. However, this constraint may exclude relevant paywalled studies and may bias the included set toward OA publication venues. This limitation is revisited in the conclusion.

2.4. Data Analysis and Insight Extraction Stage

In the final phase of Phase 7, the focus shifted to data analysis and insight generation. Selected documents were visualized to create a comprehensive report, while multi-criteria analysis evaluated the dataset to identify emerging trends in industry research. This systematic approach not only ensured methodological rigor but also strengthened the ability to identify key areas of innovation, positioning the research to make meaningful contributions to academic discourse and practical applications in the field. The stepwise methodology reflects an argumentative stance, emphasizing the need for systematic refinement to derive actionable insights from a broad dataset.

Since the relevance of AI and digital transformation research is multi-dimensional, a Multi-Criteria Decision-Making (MCDM) framework was integrated into the analysis stage [25] [26] [27]. The Multi-Criteria Analysis (MCA) enables the evaluation of studies based on key factors such as academic impact, practical applicability, and industrial readiness. This approach, derived from established MCDM techniques including AHP [28], TOPSIS, and ELECTRE [29] [30], provides a systematic weighting mechanism that balances these dimensions. Through this integration, the study extends traditional bibliometric mapping by quantifying research significance across industrial contexts, supporting more nuanced and data-driven insights.

To test robustness, sensitivity analyses were conducted using alternative weighting configurations and normalization methods [30]. Correlation and concordance checks across ranking outcomes confirmed the internal consistency of the MCA results. Furthermore, inter-rater reliability during screening was validated through iterative cross-checking between evaluators, ensuring consistent classification and minimizing subjective bias. The combination of PRISMA-based screening and MCDM-driven evaluation strengthens methodological validity, providing a reliable foundation for subsequent sectoral and temporal analyses.

For each included study (n=32), metadata and analytic fields were extracted into a standardized coding sheet, including: publication year, country/region, research method, application context, sector(s), and the study's reported AI and DT focus. Sector coding allowed multi-tag assignment when a study addressed more than one sector. The extracted dataset supported descriptive trend analysis and sectoral mapping, followed by multi-criteria evaluation of study relevance.

2.5. Multi-Criteria Analysis (MCA) for Study Relevance

Because AI–DT relevance is multidimensional, a Multi-Criteria Analysis (MCA) was used to evaluate the included studies beyond descriptive mapping. This research operationalized three criteria aligned with the study objectives:

1) C1 Academic impact: evidence of scholarly influence (e.g., citation count at the time of extraction, journal quality indicators, and/or visibility of the outlet).
2) C2 Practical relevance: clarity and strength of real-world implications, including industry use cases, implementation considerations, or organizational outcomes.

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3) C3 Sectoral readiness: evidence of deployment maturity/readiness in a sector (e.g., readiness frameworks, adoption barriers, governance requirements, or demonstrated implementation context).

Scoring rubric (0–2 scale). Each criterion was scored using an ordinal rubric:

0 = not addressed / no evidence

1 = mentioned / limited evidence

2 = substantial and explicit evidence

Weighting technique. To maintain transparency and avoid subjective overfitting, the baseline MCA used an equal-weight weighted-sum model (w1=w2=w3=1/3). Sensitivity analysis was conducted by testing alternative weighting schemes (e.g., emphasizing academic impact or readiness) to examine ranking stability across plausible scenarios.
MCA aggregation (weighted sum). For study *i*, the MCA score was computed as shown in Equation 1.

$$\mathrm{MCA}_i = \sum_{k=1}^{3} w_k \times S_{ik} \tag{1}$$

where S_{ik} is the rubric score (0–2) for criterion k.

Worked example (one-paper calculation). Assume a study receives scores: C1=2, C2=1, C3=2. With equal weights (1/3 each), as shown in Equation 2.

$$\mathrm{MCA}=\frac{1}{3}(2)+\frac{1}{3}(1)+\frac{1}{3}(2)=1.67 \tag{2}$$

This score supports comparative prioritization of studies by overall relevance while retaining interpretability of each criterion's contribution.

3. RESULTS AND DISCUSSION

This section synthesizes the findings to explicitly address the two research questions: (RQ1) how temporal trends shape AI–DT research across industries, and (RQ2) which factors drive the relevance and impact of studies based on the MCA criteria. Evidence is

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drawn from the 32 included studies and is supported by bibliometric trend visuals and sectoral mapping results.

3.1. RQ1: Temporal and thematic trends in AI–DT research

Across the reviewed evidence, AI–DT research shows a clear acceleration in recent years, indicating a growing consolidation of interest in AI-enabled transformation as a strategic lever for Industry 4.0/5.0. The temporal pattern suggests that research activity intensifies when industries face rapid disruptions and need data-driven automation, predictive decision-making, and resilient operations. This trend is reflected in the rise of studies focusing on predictive analytics, autonomous systems, and smart manufacturing-oriented transformation pathways, where AI capabilities increasingly become embedded into broader DT initiatives rather than treated as isolated technologies.

Thematically, the literature clusters around (i) operational intelligence (automation, prediction, optimization), (ii) digitally integrated service models (platforms, omnichannel experiences, AI-assisted interaction), and (iii) governance and readiness concerns (data

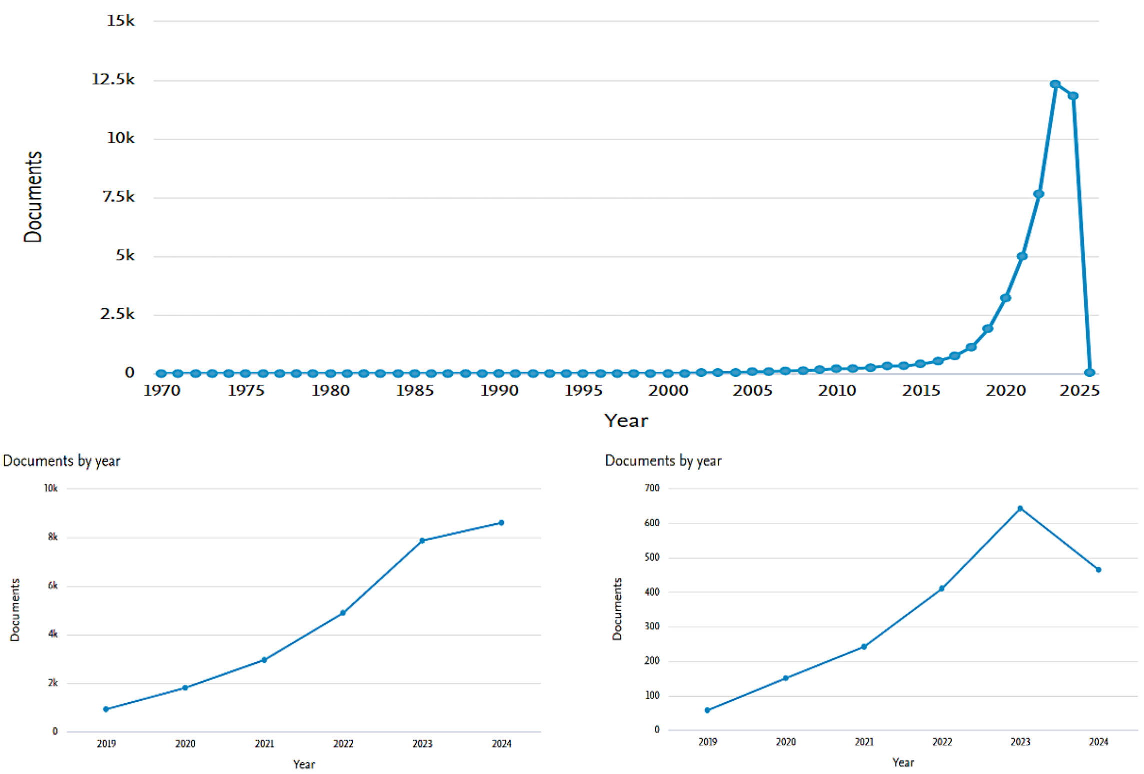

Figure. 2: Publication Growth Trend Analysis (1970–2025). Source on Scopus

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security, ethics, regulation, and organizational capabilities). Importantly, the trend is not uniform across domains: some industries demonstrate mature and repeatedly studied use cases, whereas others remain less developed and appear sporadically in the evidence base, indicating uneven research maturity and adoption trajectories.

This ranking highlights the pivotal role played by these nations in shaping the global research landscape. China's significant lead reflects its robust investment in research and development, growing scientific infrastructure, and strategic focus on technological advancement. The United States, while trailing China, continues to maintain its position as a global research powerhouse, with India and the United Kingdom also showing strong contributions. The bottom-right graph refines this analysis, offering a closer look at document counts within smaller numerical ranges. This detailed view reaffirms China's dominance while highlighting the contributions of other emerging and established nations. The stark disparities in research output across countries point to varying levels of investment in science, access to resources, and national policies promoting innovation. These insights emphasize the need for collaborative strategies to address global challenges, reduce inequities in knowledge production, and support underrepresented regions in building their research capacity. By fostering a more inclusive and equitable global research ecosystem, nations can ensure a more balanced distribution of scientific progress and innovation.

3.2. RQ2: Relevance factors and MCA-based insights

To address RQ2, relevance is interpreted through the MCA dimensions used in this study academic impact, practical relevance, and sectoral readiness. Overall, studies that score strongly tend to (a) provide clearly articulated industry implications and implementable insights, (b) demonstrate maturity or readiness context (e.g., adoption barriers, governance needs, or deployment framing), and (c) show scholarly visibility through publication venue quality and/or citation-related indicators. In other words, relevance is strongest when research simultaneously links robust academic contribution with actionable DT pathways and context-specific readiness. Sectoral mapping further indicates where research relevance concentrates. The sectoral percentages were computed by counting sector tags across the 32 included studies and normalizing the totals to 100%, allowing multi-sector tagging when a study covers more than one domain.

This approach highlights domains that repeatedly appear in AI–DT studies as more "research-saturated," while sectors with low representation can be interpreted as underexplored opportunities where future work may yield high marginal contribution especially if practical need is high but scholarly coverage is limited.

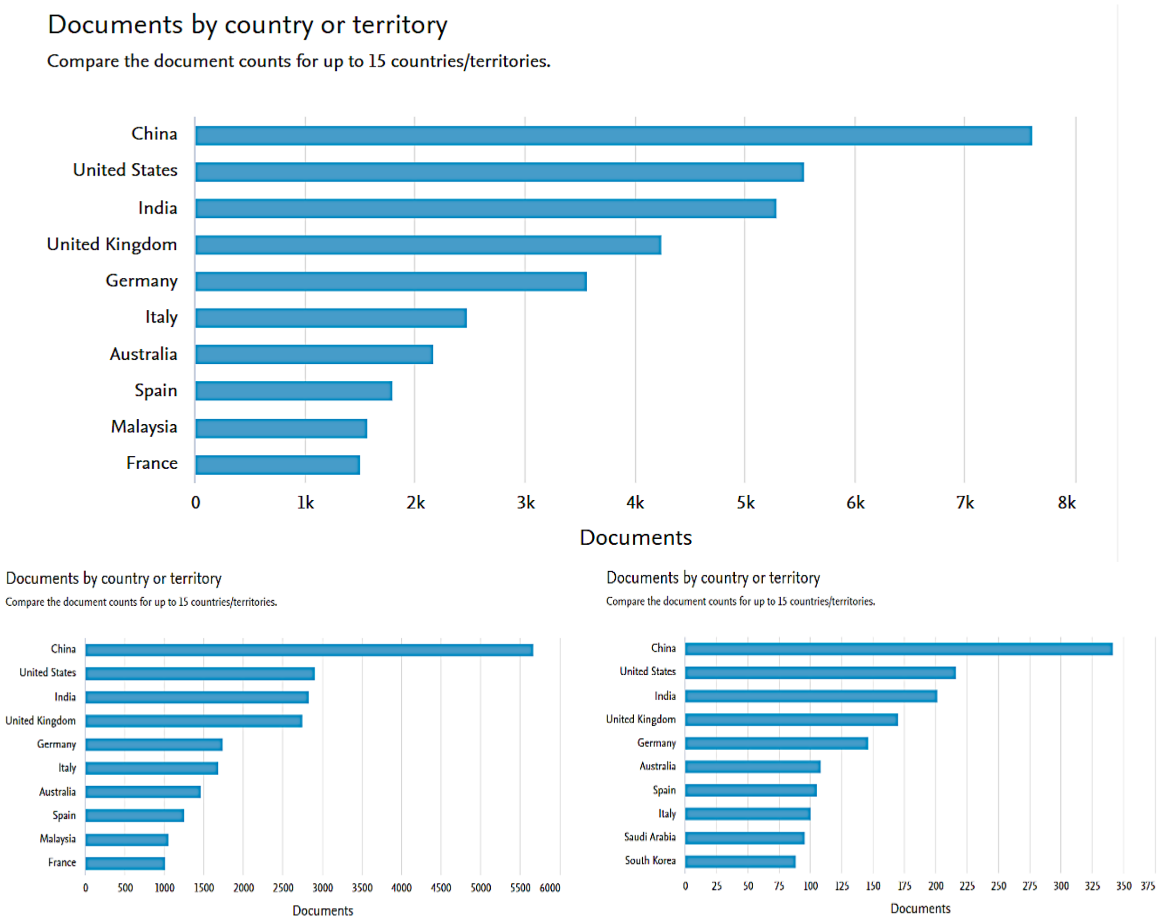

Figure. 3. Evidence (1970–2025). Source on Scopus

Figure 4 illustrates the results of a bibliometric analysis conducted to examine the processes and outcomes of a specific research domain, using VOSviewer software to effectively visualize bibliometric data. The analysis is presented in five components, each of which offers unique insights into the research landscape. The first component highlights the interconnected keyword networks in the study, revealing three main clusters: the blue cluster, related to "information"; the red cluster, related to "knowledge"; and the green cluster, related to "utilization." These clusters signify distinct but interrelated thematic areas, reflecting the conceptual framework underlying the study. The second component provides a detailed view of these relationships, allowing the

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researcher to understand the structural relationships between keywords across the clusters. Complementing this, the third component reiterates the interconnected nature of these keywords, reinforcing the consistency of the clustering patterns. The fourth component focuses on the density of this keyword network, emphasizing their interconnectedness and relative prominence in the study. Finally, the fifth component displays a heatmap representation of keyword frequency, where frequently occurring keywords are highlighted in yellow, while less common keywords are shown in blue, offering a visual hierarchy of keyword importance.

This comprehensive analysis enables researchers to derive meaningful interpretations of the data. For example, it helps in identifying the most relevant and frequently used keywords, understanding the interactions between different concepts, and determining emerging trends in the field. These insights play a vital role in refining research objectives, formulating new hypotheses, and fostering collaboration among researchers in related disciplines. Furthermore, the visualization of keyword networks and their distributions highlight potential gaps in the literature, providing a strategic basis for future research efforts. In conclusion, this bibliometric analysis not only sheds light on the thematic and structural aspects of the research but also provides researchers with a robust framework to explore under-researched areas, advance knowledge, and enhance the impact of collaborative efforts within the research community.

Table 2 shows the multi-criteria evaluation matrix for the 32 included studies. Each row represents a document, and each column represents an industry sector (e.g., finance and banking, healthcare, education, manufacturing, retail, and others). Binary values (1/0) indicate whether a study is relevant (1) or not relevant (0) to a given sector, supporting sectoral mapping across the final sample.

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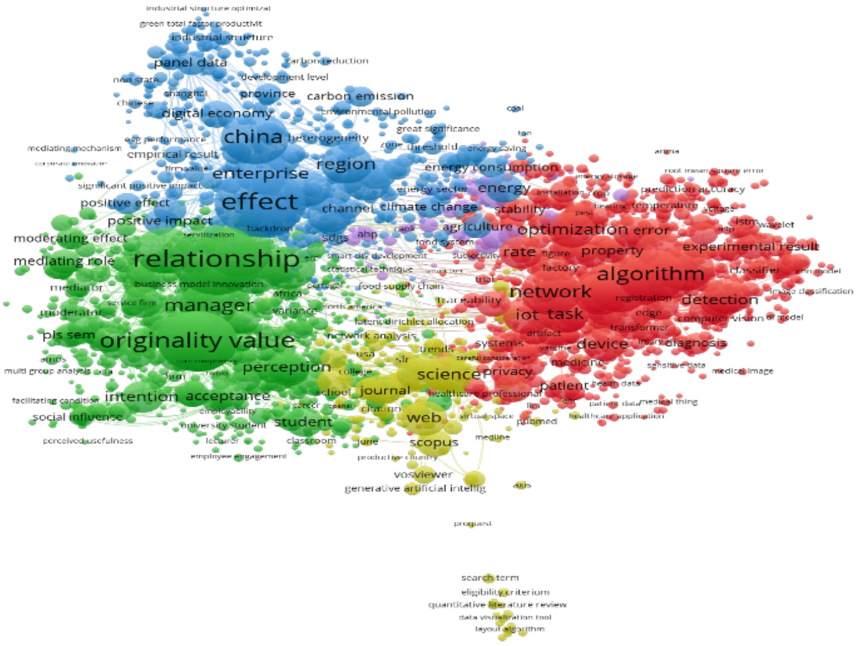
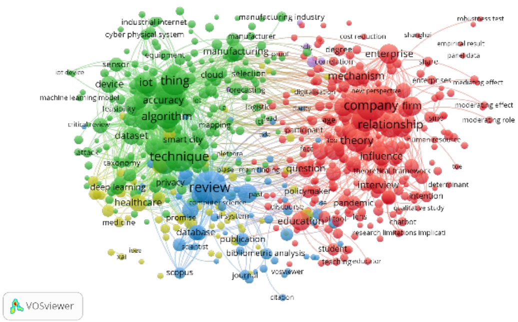
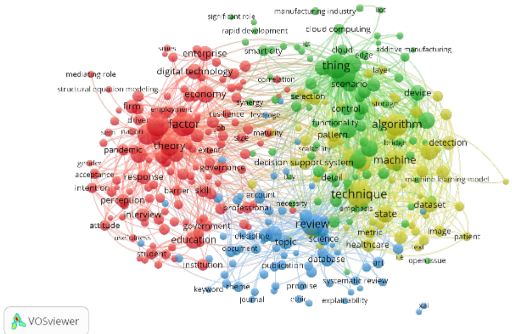


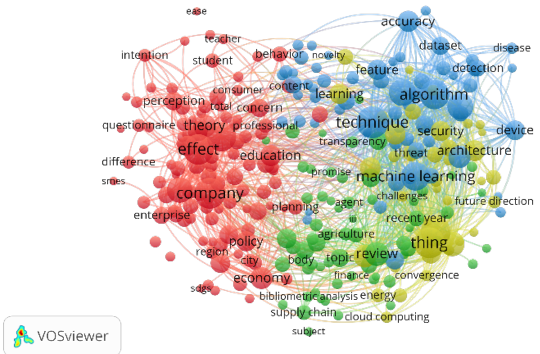
(a). RIS data extract 27,102 documents



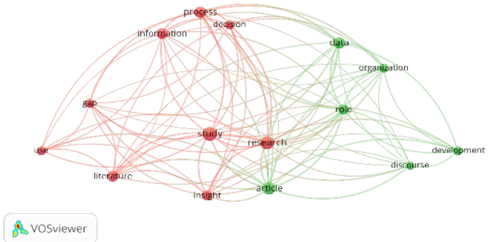
(b): RIS data extract 1,970 documents



(c): RIS data extract 1,037 documents



(d): RIS data extract 737 documents



(e): RIS data extract 32 documents

Figure. 4: Mapping Network Visualization and Keyword Frequency Mapping: Bibliometric Analysis Stage 4 to Stage 6

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Table 2. Mapping of Research Articles to Industry Sectors.

Articles	Trending Industry Research Sector
[31]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[32]	Finance and Banking, Health and Healthcare, Education, Transport and Logistics, Energy and Environment, Government and Public Sector, Telecommunications, Human Resources, Legal Sector, Insurance
[33]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications.
[34]	Health and Healthcare, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Agriculture, Government and Public Sector.
[35]	Finance and Banking, Health and Healthcare, Education, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Legal Sector.
[36]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[37]	Health and Healthcare, Manufacturing, Retail and Consumer Goods, Energy and Environment, Agriculture.
[38]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[39]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[40]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Media and Entertainment, Government and Public Sector, Telecommunications, Human Resources, Legal Sector, Insurance
[41]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Insurance

Articles	Trending Industry Research Sector
[42]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[43]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[44]	Manufacturing
[45]	Retail and Consumer Goods
[46]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[47]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[48]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector.
[49]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[50]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Government and Public Sector, Telecommunications, Human Resources, Legal Sector, Insurance
[51]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[52]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and

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Articles	Trending Industry Research Sector
	Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[53]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[54]	Health and Healthcare, Education, Retail and Consumer Goods, Media and Entertainment, Government and Public Sector, Telecommunications, Human Resources, Insurance
[55]	Finance and Banking, Retail and Consumer Goods, Agriculture, Government and Public Sector, Insurance
[56]	Finance and Banking, Health and Healthcare, Education, Retail and Consumer Goods, Transport and Logistics, Media and Entertainment, Government and Public Sector, Human Resources, Legal Sector, Insurance
[57]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Media and Entertainment, Government and Public Sector, Telecommunications, Human Resources, Insurance
[58]	Education, Media and Entertainment, Government and Public Sector.
[59]	Retail and Consumer Goods, Transport and Logistics, Agriculture.
[60]	Finance and Banking, Health and Healthcare, Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Energy and Environment, Media and Entertainment, Agriculture, Government and Public Sector, Telecommunications, Real Estate and Property Management, Human Resources, Legal Sector, Insurance
[61]	Education, Manufacturing, Retail and Consumer Goods, Transport and Logistics, Agriculture, Human Resources.
[62]	Education

The evaluation process involved applying multiple criteria across multiple dimensions to assess the relevance of each document to a specific industry, with the results highlighting areas where AI and digital transformation research has a stronger presence. For example, sectors such as Education, Finance, and Healthcare consistently emerged as highly relevant across many documents, indicating significant research focus in these areas. In contrast, other sectors such as Real Estate and Property Management and Legal Sector showed less frequent inclusion, indicating that these areas may be under-explored

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or have fewer applications of AI and digital transformation in the reviewed research. This matrix approach allows for a clearer understanding of where current research in AI and digital transformation is focused, providing a framework for identifying research gaps and areas that could benefit from further exploration. Furthermore, this evaluation helps align future research with sectors that show the greatest potential for AI applications, while highlighting industries that require further attention to maximize the impact of digital transformation in their operational processes. Comprehensive analysis of these documents through Multi-Criteria Analysis (MCA) not only helps identify trends in research but also provides valuable insights into the effectiveness and scope of digital transformation efforts across sectors, informing future research directions and practical applications.

In Figure 5, sectors such as Education, Retail and Consumer Goods, and Government and Public Sector stand out as receiving a relatively higher share of research focus, at 8%. This highlights the growing importance of addressing digital transformation, changing consumer behavior, and government adaptation to technological advancements. On the other hand, sectors such as Real Estate and Insurance attract relatively lower attention, despite their crucial role in the broader economy. The results may reflect pressing global needs (such as digital transformation in Education) and the relative developmental stage of each industry in terms of innovation and research. Additionally, it could be argued that sectors experiencing significant technological disruption or requiring urgent societal change, such as Health and Healthcare or Energy and Environment, are particularly important for academic research but may still receive relatively less resources. The distribution of research within these industries not only offers a reflection of current academic priorities but also guides industry players in understanding the focus areas that require further investment and innovation.

Digital transformation in education is increasingly driven by AI-enabled personalized learning systems, intelligent tutoring, and data-driven decision-making. Recent research highlights that machine learning and natural language processing enhance adaptive assessments, while predictive analytics optimize student retention strategies. Moreover, AI-driven virtual classrooms and learning management systems improve accessibility and inclusiveness, especially in developing regions [63] [64] [65]. The healthcare sector demonstrates one of the highest adoption levels of AI and DT technologies. AI supports diagnostic accuracy, clinical decision-making, and operational efficiency, while digital transformation enables electronic health records, telemedicine, and predictive patient management. Integrating AI with IoT and big data enhances preventive care and patient monitoring, ensuring data-driven precision healthcare [66] [67] [68]. AI and DT are revolutionizing manufacturing through automation, predictive maintenance, and digital twins. Industry 4.0 initiatives increasingly leverage intelligent robotics and smart sensors to optimize production, minimize waste, and enhance quality control. Studies emphasize that AI-driven manufacturing systems yield measurable performance gains and pave the way for human–machine collaboration in Industry 5.0 [69] [70] [71].

In retail, AI-driven digital transformation has redefined customer engagement through personalization, recommendation engines, and sentiment analytics. Predictive models enhance demand forecasting and inventory management, while chatbots and virtual assistants transform customer service. Retailers adopting AI-supported omnichannel systems report increased customer satisfaction and operational agility [72] [73] [74]. AI and DT have transformed the finance sector through algorithmic trading, fraud detection, and digital banking. Machine learning models enable real-time credit scoring, while blockchain and digital ledgers enhance transparency and security. Financial institutions increasingly deploy robotic process automation and natural language processing for efficient client interaction [75] [76] [76]. AI and DT contribute significantly to optimizing energy systems and supporting environmental sustainability. Predictive analytics improve grid stability, while smart metering and IoT enable efficient energy consumption monitoring. AI models for carbon neutrality and renewable energy integration drive the green transition across industries [77] [78] [79]. AI-based DT initiatives in government improve service delivery, policy planning, and public resource allocation. E-government platforms now leverage machine learning and analytics for data-driven governance and citizen engagement. However, ethical considerations and data security remain ongoing challenges in public sector transformation [80] [81] [82]. AI supports logistics optimization, autonomous transport, and intelligent routing. The convergence of AI with DT enables smart fleet management and dynamic supply chain reconfiguration. Research confirms that AI adoption improves route accuracy, reduces emissions, and enhances supply resilience [83] [84] [85]. In agriculture, AI-powered DT applications improve productivity, sustainability, and risk management. Smart farming integrates AI with IoT, drones, and remote sensing for soil analysis, crop prediction, and pest detection. Studies reveal that

AI adoption enhances agricultural decision-making and supports food security [86] [87] [88]. AI and DT adoption in legal and property management remain limited but rapidly emerging. Smart contracts, predictive case analysis, and AI-based valuation models represent growing applications. Integrating AI into digital legal systems enhances transparency and accelerates documentation processes [89] [90].

The findings reveal that AI and digital transformation (DT) collectively underpin the evolution of Industry 4.0 and 5.0, driving automation, connectivity, and decision intelligence across multiple industries. Education, healthcare, and manufacturing sectors exhibit mature adoption, while legal, real estate, and agricultural domains show potential for accelerated innovation. These sectoral variations emphasize the heterogeneous nature of digital readiness and the need for customized strategies to align AI capabilities with contextual industrial requirements [91] [92]. From a policy perspective, effective digital transformation requires coordinated frameworks that address governance, data protection, and ethics. International agencies, including the European Commission and the OECD, emphasize the strategic importance of AI regulation and responsible innovation [93] [94]. Similarly, the United Nations and the World Economic Forum highlight digital inclusion and cross-border collaboration as prerequisites for equitable AI adoption and sustainable digital economies [95] [96]. These initiatives underscore that successful transformation extends beyond technological readiness to encompass policy coherence, institutional support, and human capital development. Academically, the study advances understanding of how multi-criteria analysis (MCA) complements systematic literature reviews (SLR) to assess research relevance in emerging technological fields. This integrative approach offers a transferable framework that can be replicated across domains beyond AI and DT, such as cybersecurity, metaverse adoption, and sustainable innovation. Future research may explore hybrid SLR–MCDM designs integrating bibliometric indicators with text mining and natural language processing for deeper trend identification [97] [98].

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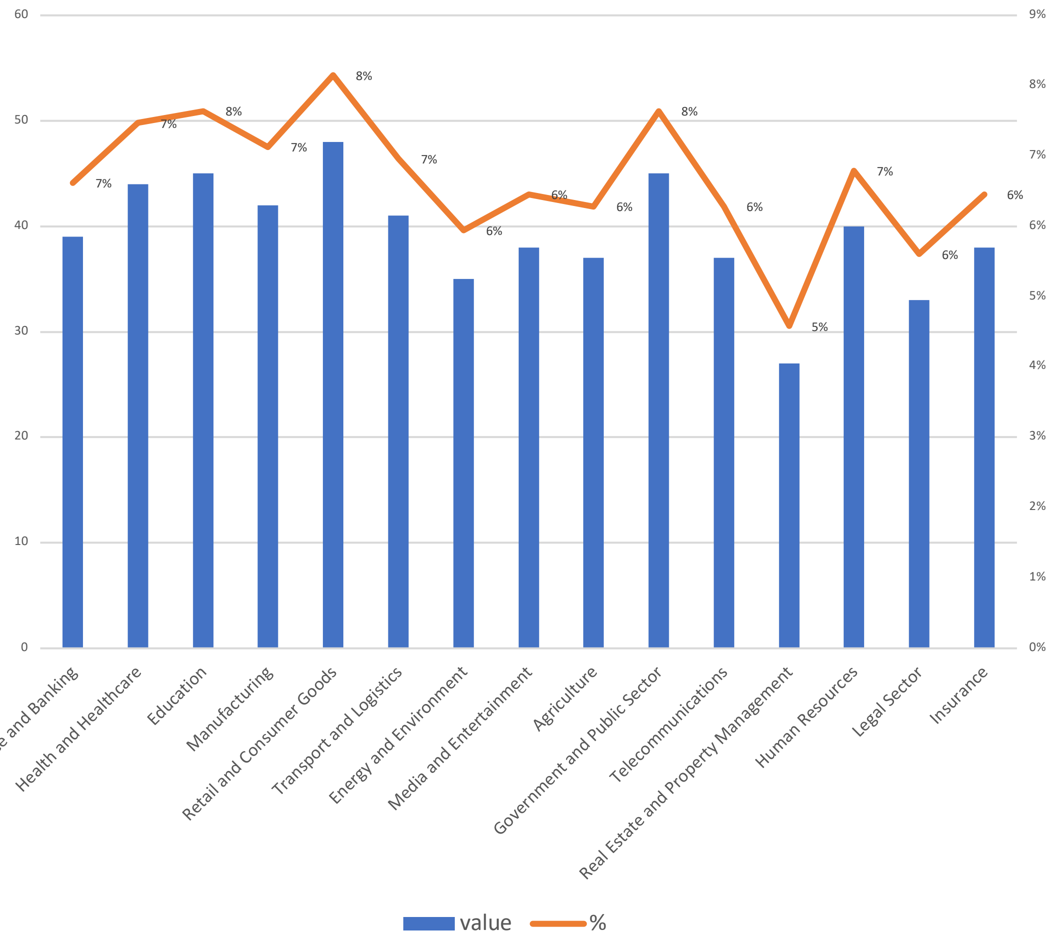

Figure. 5 Mapping Research distribution across industrial sectors

Sectoral percentages were computed by counting the number of included studies (n=32) assigned to each sector and dividing by the total number of sector assignments. When a study covered multiple sectors, each sector tag was counted once, and the totals were normalized to 100%. Practically, the findings highlight the importance of collaboration between academia, industry, and government to bridge gaps between theory and practice [99]. Encouraging knowledge exchange, public–private partnerships, and inclusive digital policies will foster resilient and adaptive ecosystems capable of thriving in the era of intelligent automation. AI and DT integration thus represent not only technological innovation but also a transformative paradigm for achieving long-term economic and social sustainability [100] [101].

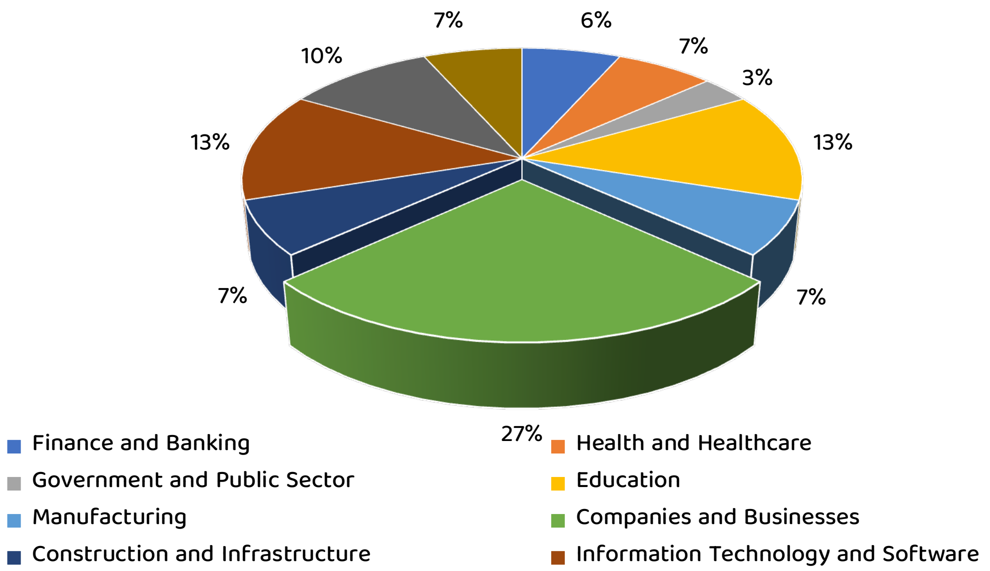

Figure. 6 Percentage share of research across industrial sectors

The analysis of trending industry research sectors reveals a broad and growing interest in AI and digital transformation across various industries, with Education, Retail and Consumer Goods, and the Government and Public Sector leading at 8% each. These sectors demonstrate a substantial focus on leveraging digital technologies to improve accessibility, consumer engagement, and the delivery of public services. The Finance and Banking, Health and Healthcare, and Telecommunications sectors, each representing 7% of the research, emphasize the role of AI in enhancing service efficiency, operational security, and communication infrastructure. However, sectors such as Real Estate and Property Management and the Legal Sector, contributing 5% and 6% respectively, indicate an underexplored potential for AI integration. This presents opportunities for future research to delve deeper into how these traditionally less-digitized sectors can benefit from digital transformation, possibly through advanced AI applications that streamline processes and enhance service delivery. Looking forward, future research must focus on expanding the scope of AI and digital transformation across all sectors, including those with less research attention, such as legal services and real estate management. Researchers should aim to explore more innovative applications that can bridge the technological gap and offer new solutions tailored to the specific challenges faced by these industries. Additionally, research can explore cross-industry collaborations that can foster knowledge exchange and accelerate digital adoption.

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The methodology applied in this study, using bibliometric analysis provides significant advantages in terms of visualizing complex networks of keywords and tracking trends over time. This approach allows researchers to identify emerging areas of interest and the evolution of research themes, offering insights that might otherwise be difficult to discern from traditional methods. The integration of keyword clustering and heat mapping enhances the precision of identifying which concepts and technologies are most prevalent, allowing for a more targeted exploration of research gaps and opportunities for future studies. Furthermore, the systematic mapping approach ensures that the research findings are grounded in data-driven analysis, making the conclusions more reliable and actionable for both academic and industry stakeholders. In summary, the increasing focus on sectors such as education, healthcare, and government in AI and digital transformation research signals a positive trajectory, but there is ample room for further exploration in other industries. The methodology used in this study, with its ability to map trends and identify clusters, offers a robust framework for future research that can guide the development of targeted, impactful digital solutions across all sectors.

4. CONCLUSION

This study mapped how research on artificial intelligence and digital transformation has evolved across industrial sectors and highlighted where evidence is most concentrated. The temporal analysis indicates a strong rise in AI–DT publications in recent years, reflecting accelerated interest in data-driven automation, intelligent decision support, and Industry 4.0/5.0 agendas. Sectoral mapping shows that education, healthcare, manufacturing, retail, and public services receive the most attention, while legal and real-estate contexts remain comparatively underexplored. Using a multi-criteria analysis, the review further shows that research relevance is not driven by academic contribution alone, but also by practical applicability and sectoral readiness. This implies that future studies should report clearer implementation context, readiness indicators, and measurable organizational impact to strengthen alignment between scholarly output and industry needs. Limitations include the reliance on a single database and the application of open-access screening, which may exclude relevant paywalled studies. Future research can extend the dataset using additional databases and enrich the analysis by combining bibliometric mapping with text-mining or topic-modeling methods.

REFERENCES

[1] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 3, pp. 18–23, 2015. doi: 10.1016/j.mfglet.2014.12.001.

[2] J. Yang, Y. Liu, and P.L. Morgan, "Human–machine interaction towards industry 5.0: human-centric smart manufacturing," *Digit. Eng.*, vol. 2, p. 100013, 2024. doi: 10.1016/j.dte.2024.100013.

[3] A. Fernández-Miguel, F.E. García-Muiña, S. Ortíz-Marcos, M. Jiménez-Calzado, A.P. del Hoyo, and D. Settembre-Blundo, "AI-driven transformations in manufacturing: bridging industry 4.0, 5.0, and 6.0 in sustainable value chains," *Future Internet*, vol. 17, no. 9, 2025. doi: 10.3390/fi17090430.

[4] I. Abbes, "Strategic pathways for innovation and sustainability in digital transformation: insights from leading global companies," *Soc. Sci. Humanit. Open*, vol. 12, p. 101906, 2025. doi: 10.1016/j.ssaho.2025.101906.

[5] M. Ghobakhloo, H.A. Mahdiraji, M. Iranmanesh, and V. Jafari-Sadeghi, "From industry 4.0 digital manufacturing to industry 5.0 digital society: a roadmap toward human-centric, sustainable, and resilient production," *Inf. Syst. Front.*, 2024. doi: 10.1007/s10796-024-10476-z.

[6] Y.K. Dwivedi, L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, Y. Duan, R. Dwivedi, J. Edwards, A. Eirug, V. Galanos, P.V. Ilavarasan, M. Janssen, P. Jones, A.K. Kar, H. Kizgin, B. Kronemann, B. Lal, B. Lucini, R. Medaglia, K. Le Meunier-FitzHugh, L.C. Le Meunier-FitzHugh, S. Misra, E. Mogaji, S.K. Sharma, J.B. Singh, V. Raghavan, R. Raman, N.P. Rana, S. Samothrakis, J. Spencer, K. Tamilmani, A. Tubadji, P. Walton, and M.D. Williams, "Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," *Int. J. Inf. Manage.*, vol. 57, p. 101994, 2021. doi: 10.1016/j.ijinfomgt.2019.08.002.

[7] A. Belhadi, M. Venkatesh, S. Kamble, and M.Z. Abedin, "Data-driven digital transformation for supply chain carbon neutrality: insights from cross-sector supply chain," *Int. J. Prod. Econ.*, vol. 270, 2024. doi: 10.1016/j.ijpe.2024.109178.

[8] M. Soori, B. Arezoo, and R. Dastres, "Digital twin for smart manufacturing, a review," *Sustainable Manuf. Serv. Econ.*, vol. 2, p. 100017, 2023. doi: 10.1016/j.smse.2023.100017.

[9] M.G. Belu, and A.M. Marinoiu, "AI-enabled supply chain management: a bibliometric analysis using VOSviewer and RStudio bibliometrix software tools," *Sustainability*, vol. 17, no. 5, 2025. doi: 10.3390/su17052092.

[10] P. Onu, A. Pradhan, N.S. Madonsela, S.A. Ajayi, C.O. Osueke, D.R. Samuel, and S. Adebayo, "Integration of AI and IoT in smart manufacturing: exploring technological, ethical, and legal frontiers," *Procedia Comput. Sci.*, vol. 253, pp. 654–660, 2025. Doi: 10.1016/j.procs.2025.01.127.

[11] G. Vial, "Understanding digital transformation: a review and a research agenda," *J. Strateg. Inf. Syst.*, vol. 28, no. 2, pp. 118–144, 2019. doi: 10.1016/j.jsis.2019.01.003.

[12] P.C. Verhoef, T. Broekhuizen, Y. Bart, A. Bhattacharya, J. Qi Dong, N. Fabian, and M. Haenlein, "Digital transformation: a multidisciplinary reflection and research agenda," *J. Bus. Res.*, vol. 122, pp. 889–901, 2021. doi: 10.1016/j.jbusres.2019.09.022.

[13] A. Schumacher, S. Erol, and W. Sihn, "A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises," *Procedia CIRP*, vol. 52, pp. 161–166, 2016. doi: 10.1016/j.procir.2016.07.040.

[14] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J.M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting, and D. Moher, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *BMJ*, vol. 372, 2021. doi: 10.1136/bmj.n71.

[15] V. Dolci, B. Bigliardi, A. Petroni, B. Pini, S. Filippelli, and L. Tagliente, "Integrating industry 4.0 and circular economy: a conceptual framework for sustainable manufacturing," *Procedia Comput. Sci.*, vol. 232, pp. 1711–1720, 2024. doi: 10.1016/j.procs.2024.01.169.

[16] Y. Gao, S. Liu, and L. Yang, "Artificial intelligence and innovation capability: a dynamic capabilities perspective," *Int. Rev. Econ. Finance*, vol. 98, p. 103923, 2025. doi: 10.1016/j.iref.2025.103923.

[17] A. Aldoseri, K.N. Al-Khalifa, and A.M. Hamouda, "AI-powered innovation in digital transformation: key pillars and industry impact," *Sustainability*, vol. 16, no. 5, p. 1790, 2024. doi: 10.3390/su16051790.

[18] D. Moher, A. Liberati, J. Tetzlaff, and D.G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement," *BMJ*, vol. 339, 2009. doi: 10.1136/bmj.b2535.

[19] D. Tranfield, D. Denyer, and P. Smart, "Towards a methodology for developing evidence-informed management knowledge by means of systematic review," *Br. J. Manag.*, vol. 14, no. 3, pp. 207–222, 2003. doi: 10.1111/1467-8551.00375.

[20] C. Wohlin, E. Mendes, K.R. Felizardo, and M. Kalinowski, "Guidelines for the search strategy to update systematic literature reviews in software engineering," *Inf. Softw. Technol.*, vol. 127, p. 106366, 2020. doi: 10.1016/j.infsof.2020.106366.

[21] H. Snyder, "Literature review as a research methodology: an overview and guidelines," *J. Bus. Res.*, vol. 104, pp. 333–339, 2019. doi: 10.1016/j.jbusres.2019.07.039.

[22] A. Carrera-Rivera, W. Ochoa, F. Larrinaga, and G. Lasa, "How-to conduct a systematic literature review: a quick guide for computer science research," *MethodsX*, vol. 9, p. 101895, 2022. doi: 10.1016/j.mex.2022.101895.

[23] J. Stofkova, M. Krejnus, K.R. Stofkova, P. Malega, and V. Binasova, "Use of the analytic hierarchy process and selected methods in the managerial decision-making process in the context of sustainable development," *Sustainability*, vol. 14, no. 18, 2022. doi: 10.3390/su141811546.

[24] Y. Qin, Q. Qi, P. Shi, S. Lou, P.J. Scott, and X. Jiang, "Multi-attribute decision-making methods in additive manufacturing: the state of the art," *Processes*, vol. 11, no. 2, 2023. doi: 10.3390/pr11020497.

[25] S. Malefaki, D. Markatos, A. Filippatos, and S. Pantelakis, "A comparative analysis of multi-criteria decision-making methods and normalization techniques in holistic sustainability assessment for engineering applications," *Aerospace*, vol. 12, no. 2, 2025. doi: 10.3390/aerospace12020100.

[26] K. Govindan, and M.B. Jepsen, "ELECTRE: a comprehensive literature review on methodologies and applications," *Eur. J. Oper. Res.*, vol. 250, no. 1, pp. 1–29, 2016. doi: 10.1016/j.ejor.2015.07.019.

[27] S. Greco, M. Ehrgott, and J.R. Figueira, "Multiple Criteria Decision Analysis," 2nd ed., Springer, New York, NY, 2016.

[28] A. Mardani, A. Jusoh, K.M.D. Nor, Z. Khalifah, N. Zakwan, and A. Valipour, "Multiple criteria decision-making techniques and their applications – a review of the literature from 2000 to 2014," *Econ. Res.-Ekonomska Istraživanja*, vol. 28, no. 1, pp. 516–571, 2015. doi: 10.1080/1331677X.2015.1075139.

[29] A.A. Khanfar, R. Kiani Mavi, M. Iranmanesh, and D. Gengatharen, "Determinants of artificial intelligence adoption: research themes and future directions," *Inf. Technol. Manag.*, 2024. doi: 10.1007/s10799-024-00435-0.

[30] R. Santos, B. Veloso, and P. Popoli, "The use of AI in government and its risks: lessons from the private sector," 2024. doi: 10.1108/TG-02-2024-0038.

[31] M. Ghobakhloo, M. Iranmanesh, B. Foroughi, M.L. Tseng, D. Nikbin, and A.A.A. Khanfar, "Industry 4.0 digital transformation and opportunities for supply chain resilience: a comprehensive review and a strategic roadmap," *Prod. Plan. Control*, vol. 0, no. 0, pp. 1–31, 2023. doi: 10.1080/09537287.2023.2252376.

[32] M. Deveci, "Effective use of artificial intelligence in healthcare supply chain resilience using fuzzy decision-making model," *Soft Comput.*, vol. 2, 2023. doi: 10.1007/s00500-023-08906-2.

[33] G. Iazzolino, and N. Stremlau, "AI for social good and the corporate capture of global development," *Inf. Technol. Dev.*, pp. 1–18, 2024. doi: 10.1080/02681102.2023.2299351.

[34] H. Heimberger, D. Horvat, and F. Schultmann, "Exploring the factors driving AI adoption in production: a systematic literature review and future research agenda," *Inf. Technol. Manag.*, vol. 0, no. 0, 2024. doi: 10.1007/s10799-024-00436-z.

[35] M. Sonntag, S. Mehmann, J. Mehmann, and F. Teuteberg, "Development and evaluation of a maturity model for AI deployment capability of manufacturing companies," *Inf. Syst. Manag.*, vol. 00, no. 00, pp. 1–31, 2024. doi: 10.1080/10580530.2024.2319041.

[36] H. Fredrik, H. Elise, L. Patrick, and M. Najwa, "Understanding artificial intelligence diffusion through an AI capability maturity model," *Inf. Syst. Front.*, pp. 1–18, 2024. doi: 10.1007/s10796-024-10528-4.

[37] J. Koponen, S. Julkunen, A. Laajalahti, M. Turunen, and B. Spitzberg, "Work characteristics needed by middle managers when leading AI-integrated service teams," vol. 0, no. 0, pp. 1–18, 2023. doi: 10.1177/10946705231220462.

[38] T. Carstensen, and K. Ganz, "Gendered AI: German news media discourse on the future of work," *AI Soc.*, pp. 1–18, 2023. doi: 10.1007/s00146-023-01747-5.

[39] M.R.M.M.B. Mujahid Mohiuddin Babu Shahriar Akter, and D. Hack-Polay, "The role of artificial intelligence in shaping the future of agile fashion industry," *Prod. Plan. Control*, vol. 35, no. 15, pp. 2084–2098, 2024. doi: 10.1080/09537287.2022.2060858.

[40] D. Joshi, "AI governance in India–law, policy and political economy," *Commun. Res. Pract.*, vol. 10, no. 3, pp. 328–339, 2024. doi: 10.1080/22041451.2024.2346428.

[41] M. Uddin, M. Obaidat, S. Manickam, S.U.A. Laghari, A. Dandoush, H. Ullah, and S.S. Ullah, "Exploring the convergence of metaverse, blockchain, and AI: a comprehensive survey of enabling technologies, applications, challenges, and future directions," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, 2024. doi: 10.1002/widm.1556.

[42] A. Puthanveettil Madathil, X. Luo, Q. Liu, C. Walker, R. Madarkar, Y. Cai, Z. Liu, W. Chang, and Y. Qin, "Intrinsic and post-hoc XAI approaches for fingerprint identification and response prediction in smart manufacturing processes," *J. Intell. Manuf.*, 2024. doi: 10.1007/s10845-023-02266-2.

[43] D.S.H. Manzo, Y. Jiang, E. Elyan, and J. Isaacs, "Artificial intelligence-based conversational agents used for sustainable fashion: systematic literature review," *Int. J. Hum. Comput. Interact.*, vol. 0, no. 0, pp. 1–13, 2024. doi: 10.1080/10447318.2024.2352920.

[44] S. Sai, R. Sai, and V. Chamola, "Generative AI for industry 5.0: analyzing the impact of ChatGPT, DALL·E, and other models," *IEEE Open J. Commun. Soc.*, vol. PP, p. 1, 2024. doi: 10.1109/OJCOMS.2024.3400161.

[45] M. Winkel, "Controlling the uncontrollable: the public discourse on artificial intelligence between the positions of social and technological determinism," *AI Soc.*, 2024. doi: 10.1007/s00146-024-01979-z.

[46] E. Aydin, M. Rahman, and E. Ozeren, "Does industry 5.0 reproduce gender (in)equalities at organizations? understanding the interaction of human resources and software development teams in supplying human capitals," *Inf. Syst. Front.*, 2023. doi: 10.1007/s10796-023-10450-1.

[47] R.S. Peres, X. Jia, J. Lee, K. Sun, A.W. Colombo, and J. Barata, "Industrial artificial intelligence in industry 4.0 -systematic review, challenges and outlook," *IEEE Access*, vol. 0, pp. 3042874, 2020. doi: 10.1109/ACCESS.2020.3042874.

[48] T. Mettler, "The connected workplace: characteristics and social consequences of work surveillance in the age of datification, sensorization, and artificial intelligence," *J. Inf. Technol.*, vol. 39, no. 3, pp. 547–567, 2024.

[49] M. Blaurock, M. Büttgen, and J. Schepers, "Designing collaborative intelligence systems for employee-AI service co-production," *J. Serv. Res.*, vol. 0, no. 0, pp. 1–19, 2024. doi: 10.1177/10946705241238751.

[50] A. Masso, A. Kaun, and C. van Noordt, "Basic values in artificial intelligence: comparative factor analysis in Estonia, Germany, and Sweden," *AI Soc.*, pp. 1–18, 2023. doi: 10.1007/s00146-023-01750-w.

[51] M.F. de-Lima-Santos, W.N. Yeung, and T. Dodds, "Guiding the way: a comprehensive examination of AI guidelines in global media," *AI Soc.*, 2024. doi: 10.1007/s00146-024-01973-5.

[52] K. Kiuchi, K. Otsu, and Y. Hayashi, "Psychological insights into the research and practice of embodied conversational agents, chatbots and social assistive robots: a systematic meta-review," *Behav. Inf. Technol.*, 2023. doi: 10.1080/0144929X.2023.2286528.

[53] N. De la Peña, and O.M. Granados, "Artificial intelligence solutions to reduce information asymmetry for Colombian cocoa small-scale farmers," *Inf. Process. Agric.*, vol. 11, no. 3, pp. 310–324, 2024. doi: 10.1016/j.inpa.2023.03.001.

[54] K. Feher, L. Vicsek, and M. Deuze, "Modeling AI trust for 2050: perspectives from media and info-communication experts," *AI Soc.*, pp. 1–18, 2024. doi: 10.1007/s00146-023-01827-6.

[55] J. Nesterak, "Workplace performance measurement: digitalization of work observation and analysis," 2024. doi: 10.1007/s10845-024-02419-x.

[56] G. Griffin, E. Wennerström, and A. Foka, "AI and Swedish heritage organisations: challenges and opportunities," *AI Soc.*, vol. 39, no. 5, pp. 2359–2372, 2023. doi: 10.1007/s00146-023-01689-y.

[57] I.B. Youssra Riahi Tarik Saikouk, and S.F. Wamba, "Researched topics, patterns, barriers and enablers of artificial intelligence implementation in supply chain: a latent-Dirichlet-allocation-based topic-modelling and expert validation," *Prod. Plan. Control*, vol. 0, no. 0, pp. 1–28, 2023. doi: 10.1080/09537287.2023.2286523.

[58] J.Y. Jung, T. Steinberger, and C. So, "Towards actionable data science: domain experts as end-users of data science systems," *Comput. Supported Coop. Work (CSCW)*, vol. 33, no. 3, pp. 389–433, 2024. doi: 10.1007/s10606-023-09475-6.

[59] A. Gutiérrez, J. Aguilar, A. Ortega, and E. Montoya, "Autonomous cycles of data analysis tasks for innovation processes in MSMEs," *Appl. Comput. Informatics*, 2022. doi: 10.1108/ACI-02-2022-0048.

[60] M.P. Rojas, and A. Chiappe, "Artificial intelligence and digital ecosystems in education: a review," *Technol. Knowl. Learn.*, 2024. doi: 10.1007/s10758-024-09732-7.

[61] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, and T. Vasileva, "AI-driven adaptive learning for sustainable educational transformation," *Sustainable Dev.*, vol. 33, no. 2, pp. 1921–1947, 2025. doi: 10.1002/sd.3221.

[62] M. Madanchian, and H. Taherdoost, "Decision-making criteria for AI tools in digital education," *Digit. Eng.*, p. 100069, 2025. doi: 10.1016/j.dte.2025.100069.

[63] M. Deveci, "Effective use of artificial intelligence in healthcare supply chain resilience using fuzzy decision-making model," *Soft Comput.*, vol. 2, 2023. doi: 10.1007/s00500-023-08906-2.

[64] Á. Periáñez, A.F. Del Río, I. Nazarov, E. Jané, M. Hassan, A. Rastogi, and D. Tang, "The digital transformation in health: how AI can improve the performance of health systems," *Health Syst. Reform*, vol. 10, no. 2, p. 2387138, 2024. doi: 10.1080/23288604.2024.2387138.

[65] B.Z. Wubineh, F.G. Deriba, and M.M. Woldeyohannis, "Exploring the opportunities and challenges of implementing artificial intelligence in healthcare: a systematic literature review," *Urol. Oncol. Semin. Orig. Investig.*, vol. 42, no. 3, pp. 48–56, 2024. doi: 10.1016/j.urolonc.2023.11.019.

[66] A. Belhadi, M. Venkatesh, S. Kamble, and M.Z. Abedin, "Data-driven digital transformation for supply chain carbon neutrality: insights from cross-sector supply chain," *Int. J. Prod. Econ.*, vol. 270, p. 109178, 2024. doi: 10.1016/j.ijpe.2024.109178.

[67] M. Ghobakhloo, M. Iranmanesh, B. Foroughi, M.L. Tseng, D. Nikbin, and A.A.A. Khanfar, "Industry 4.0 digital transformation and opportunities for supply chain resilience: a comprehensive review and a strategic roadmap," *Prod. Plan. Control*, vol. 0, no. 0, pp. 1–31, 2023. doi: 10.1080/09537287.2023.2252376.

[68] E. Peretz-Andersson, S. Tabares, P. Mikalef, and V. Parida, "Artificial intelligence implementation in manufacturing SMEs: a resource orchestration approach," *Int. J. Inf. Manage.*, vol. 77, p. 102781, 2024. doi: 10.1016/j.ijinfomgt.2024.102781.

[69] D.S.H. Manzo, Y. Jiang, E. Elyan, and J. Isaacs, "Artificial intelligence-based conversational agents used for sustainable fashion: systematic literature review," *Int. J. Hum. Comput. Interact.*, vol. 0, no. 0, pp. 1–13, 2024. doi: 10.1080/10447318.2024.2352920.

[70] J. Robertson, E. Botha, K. Oosthuizen, and M. Montecchi, "Managing change when integrating artificial intelligence (AI) into the retail value chain: the AI implementation compass," *J. Bus. Res.*, vol. 189, p. 115198, 2025. doi: 10.1016/j.jbusres.2025.115198.

[71] J. Yin, X. Qiu, and Y. Wang, "The impact of AI-personalized recommendations on clicking intentions: evidence from Chinese e-commerce," *J. Theor. Appl. Electron. Commer. Res.*, vol. 20, no. 1, p. 10021, 2025. doi: 10.3390/jtaer20010021.

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[72] M. Adnan, I. Ahmed, S. Iqbal, M.R. Fazal, S.J. Siddiqi, and M. Tariq, "Exploring the convergence of metaverse, blockchain, artificial intelligence, and digital twin for pioneering the digitization in the envision smart grid 3.0," *Comput. Electr. Eng.*, vol. 120, p. 109709, 2024. doi: 10.1016/j.compeleceng.2024.109709.

[73] E. Baffour Gyau, M. Appiah, B.A. Gyamfi, T. Achie, and M.A. Naeem, "Transforming banking: examining the role of AI technology innovation in boosting banks' financial performance," *Int. Rev. Fin. Anal.*, vol. 96, p. 103700, 2024. doi: 10.1016/j.irfa.2024.103700.

[74] K. Spanaki, D. Dennehy, T. Papadopoulos, and R. Dubey, "Data-driven digital transformation in operations and supply chain management," *Int. J. Prod. Econ.*, vol. 284, p. 109599, 2025. doi: 10.1016/j.ijpe.2025.109599.

[75] Preethi, M.M. Ulla, S. R, R. Devadas, Priya, and A. B J, "Green IoT: AI-powered solutions for sustainable energy management in smart devices," *Procedia Comput. Sci.*, vol. 258, pp. 2312–2322, 2025. doi: 10.1016/j.procs.2025.04.486.

[76] V.K. Sharma, G. Monteleone, G. Braccio, C.N. Anyanwu, and N.N. Aneke, "A comprehensive review of green energy technologies: towards sustainable clean energy transition and global net-zero carbon emissions," *Processes*, vol. 13, no. 1, p. 1069, 2025. doi: 10.3390/pr13010069.

[77] T. Szadeczky, and Z. Bederna, "Risk, regulation, and governance: evaluating artificial intelligence across diverse application scenarios," *Security J.*, vol. 38, no. 1, p. 35, 2025. doi: 10.1057/s41284-025-00495-z.

[78] S.A.A. Bokhari, S.Y. Park, and S. Manzoor, "Digital government transformation through artificial intelligence: the mediating role of stakeholder trust and participation," *Digital*, vol. 5, no. 3, p. 43, 2025. doi: 10.3390/digital5030043.

[79] Y. Zhang, and Y. Li, "The impact of artificial intelligence on government digital service capacity," *Int. Rev. Econ. Finance*, vol. 102, p. 104374, 2025. doi: 10.1016/j.iref.2025.104374.

[80] A. Barsekh-Onji, Z. Torres Hernandez, and E.O. Cardoso Espinosa, "Advancing smart public administration: challenges and benefits of artificial intelligence," *Urban Govern.*, vol. 5, no. 3, pp. 279–292, 2025. doi: 10.1016/j.ugj.2025.06.003.

[81] F. Sunmola, and G. Baryannis, "Artificial intelligence opportunities for resilient supply chains," *IFAC-PapersOnLine*, vol. 58, no. 19, pp. 813–818, 2024. doi: 10.1016/j.ifacol.2024.09.195.

[82] H. Pan, N. Zou, R. Wang, J. Ma, and D. Liu, "Artificial intelligence usage and supply chain resilience: an organizational information processing theory perspective," *Systems*, vol. 13, no. 9, p. 724, 2025. doi: 10.3390/systems13090724.

[83] G. Gupta, and S. Kumar Pal, "Applications of AI in precision agriculture," *Discover Agric.*, vol. 3, no. 1, p. 61, 2025. doi: 10.1007/s44279-025-00220-9.

[84] M. Ansarinejad, K. Ansarinejad, P. Lu, Y. Huang, and D. Tolliver, "Autonomous vehicles in rural areas: a review of challenges, opportunities, and solutions," *Appl. Sci.*, vol. 15, no. 8, p. 4195, 2025. doi: 10.3390/app15084195.

[85] T. Miller, G. Mikiciuk, I. Durlik, M. Mikiciuk, A. Łobodzińska, and M. Śnieg, "The IoT and AI in agriculture: the time is now—a systematic review of smart sensing technologies," *Sensors*, vol. 25, no. 12, p. 3583, 2025. doi: 10.3390/s25123583.

[86] A. Khoirun, and N. Í. ½í ¶□, "The prospect of AI law in the Indonesian legal system: present and future challenges," *Indones. J. Int. Clin. Legal Educ.*, vol. 6, no. 1, pp. 25–48, 2024. doi: 10.15294/ijicle.v6i1.4686.

[87] B. Al-haimi, H. Khalid, N.H. Zakaria, and T.H. Jasimin, "Digital transformation in the real estate industry: a systematic literature review of current technologies, benefits, and challenges," *Int. J. Inf. Manage. Data Insights*, vol. 5, no. 1, p. 100340, 2025. doi: 10.1016/j.jjimei.2025.100340.

[88] I.F. Aldhi, F. Suhariadi, E. Rahmawati, E. Supriharyanti, D. Hardaningtyas, R. Sugiarti, and A. Abbas, "Bridging digital gaps in smart city governance: the mediating role of managerial digital readiness and the moderating role of digital leadership," *Smart Cities*, vol. 8, no. 4, p. 117, 2025. doi: 10.3390/smartcities8040117.

[89] J. Barata, and I. Kayser, "Industry 5.0 – past, present, and near future," *Procedia Comput. Sci.*, vol. 219, pp. 778–788, 2023. doi: 10.1016/j.procs.2023.01.351.

[90] OECD, "OECD Digital Education Outlook 2023," *OECD*, 2023. doi: 10.1787/c74f03de-en.

[91] C. Cancela-Outeda, "The EU's AI Act: a framework for collaborative governance," *Internet Things*, vol. 27, p. 101291, 2024. doi: 10.1016/j.iot.2024.101291.

[92] E. Papagiannidis, P. Mikalef, and K. Conboy, "Responsible artificial intelligence governance: a review and research framework," *J. Strateg. Inf. Syst.*, vol. 34, no. 2, p. 101885, 2025. doi: 10.1016/j.jsis.2024.101885.

[93] Y.K. Dwivedi, A. Sharma, N.P. Rana, M. Giannakis, P. Goel, and V. Dutot, "Evolution of artificial intelligence research in technological forecasting and social change: research topics, trends, and future directions," *Technol. Forecast. Soc. Change*, vol. 192, p. 122579, 2023. doi: 10.1016/j.techfore.2023.122579.

[94] A. Yuniawan, H. Hersugondo, F. Mas'ud, H. Latan, and D.W.S. Renwick, "Determinants of artificial intelligence adoption in the financial services industry: understanding employees' perspectives," *Int. J. Inf. Manage. Data Insights*, vol. 5, no. 2, p. 100371, 2025. doi: 10.1016/j.jjimei.2025.100371.

[95] G. Baptista, and A. Pereira, "Understanding the determinants of adoption and intention to recommend AI technology in travel and transportation," *Tourism Hosp.*, vol. 6, no. 2, p. 54, 2025. doi: 10.3390/tourhosp6020054.

[96] M. and G.A. Schröder Antonius Johannes and Cuypers, "From Industry 4.0 to Industry 5.0: The Triple Transition Digital, Green and Social," in: A.J. and A.L. and B.C. and C.V. and G.A. and W.M. Stroud Dean and Schröder (Ed.), *Industry 4.0 and the Road to Sustainable Steelmaking in Europe: Recasting the Future*, Springer International Publishing, Cham, 2024, pp. 35–51. doi: 10.1007/978-3-031-35479-3_3.

[97] M. Piccarozzi, L. Silvestri, C. Silvestri, and A. Ruggieri, "Roadmap to industry 5.0: enabling technologies, challenges, and opportunities towards a holistic definition in management studies," *Technol. Forecast. Soc. Change*, vol. 205, p. 123467, 2024. doi: 10.1016/j.techfore.2024.123467.

[98] M.C. Zizic, M. Mladineo, N. Gjeldum, and L. Celent, "From industry 4.0 towards industry 5.0: a review and analysis of paradigm shift for the people, organization and technology," *Energies (Basel)*, vol. 15, no. 14, p. 5221, 2022. doi: 10.3390/en15145221.