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Research Advancements in Digital Twin Technology for Smart Manufacturing

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ABSTRACT

This study presents a comprehensive bibliometric analysis of research developments in Digital Twin (DT) technology within the domain of smart manufacturing. Drawing on Scopus-indexed publications from 2010 to 2024, the study explores the growth patterns, thematic structures, institutional contributions, collaborative networks, and emerging research trends using VOSviewer. The findings reveal a sharp increase in publication volume, particularly in 2024, indicating growing academic and industrial interest. China dominates the research landscape in terms of both institutional productivity and international collaboration, followed by India and the United States. Keyword co-occurrence analysis identifies “smart manufacturing,” “digital twin,” and “industry 4.0” as core themes, with increasing emphasis on artificial intelligence, optimization, collaborative robots, and Industry 5.0 in recent years. Co-authorship and country collaboration maps illustrate dense scholarly networks centered around prominent authors and regions. Despite significant progress, the study identifies gaps in real-world implementation, standardization, and ethical considerations. These insights offer valuable direction for future interdisciplinary research and policy strategies aimed at integrating DT technologies into next-generation manufacturing ecosystems.

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1. INTRODUCTION

The emergence of Industry 4.0 has catalyzed a paradigm shift in manufacturing, bringing forth advanced digital technologies that integrate cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), and data analytics into production environments. Among these innovations, Digital Twin (DT) technology has garnered significant attention as a transformative enabler for smart manufacturing systems. A Digital Twin refers to a dynamic, virtual representation of a physical system, process, or product that mirrors its real-time behavior through continuous data exchange [1]. This convergence of the physical and digital realms enables manufacturers to simulate, monitor, and optimize operations in real-time, thereby enhancing efficiency, predictive maintenance, and system flexibility [2].

The origin of the Digital Twin concept can be traced back to NASA’s Apollo program, where virtual models of spacecraft were created to simulate and test mission scenarios. However, its modern application in the industrial domain has only become feasible with the maturation of enabling technologies such as cloud computing, sensor networks, and real-time analytics [3]. In the context of smart manufacturing, Digital Twins are increasingly utilized to support end-to-end process visibility, lifecycle management, and product customization. They facilitate the virtualization of production lines, allowing for scenario testing, fault detection, and rapid prototyping without disrupting physical systems [4].

Research and industrial adoption of Digital Twin technology have accelerated rapidly, driven by the need for agile and resilient manufacturing systems. The COVID-19 pandemic further underscored the necessity of digital flexibility, where remote monitoring, simulation, and data-driven decision-making became critical for business continuity [5]. Digital Twins have been instrumental in addressing these needs by enabling remote diagnostics, decentralized production control, and real-time synchronization between design and production phases. This technological advancement supports not only operational excellence but also aligns with sustainability goals by reducing material waste and energy consumption [6].

Despite the promising benefits, implementing Digital Twins in manufacturing remains a complex endeavor involving multidisciplinary integration. Creating high-fidelity digital models requires accurate data acquisition, semantic interoperability, and computational efficiency to ensure that real-world behavior is accurately mirrored and predicted [7]. Moreover, the integration of DTs with IoT platforms, machine learning algorithms, and enterprise resource planning (ERP) systems demands robust architectural frameworks and security protocols. These challenges are compounded by domain-specific variations in processes, assets, and data structures, necessitating tailored solutions for each manufacturing environment.

The academic and industrial discourse on Digital Twins has expanded significantly over the past decade, with bibliometric evidence pointing to exponential growth in related publications and patents [8]. Studies have explored a variety of use cases including predictive maintenance, human-machine collaboration, digital supply chains, and adaptive quality control. While early research focused primarily on technical modeling and simulation, contemporary studies increasingly emphasize DT deployment frameworks, data governance models, and integration strategies with other Industry 4.0 technologies. These research trends indicate a transition from conceptual exploration toward operational realization, signaling the maturation of the field.

Despite the growing body of literature, key gaps persist in understanding how Digital Twin technology is evolving within the specific domain of smart manufacturing. The existing research is fragmented across disciplines such as mechanical engineering, computer science, and industrial management, often lacking a unified synthesis of insights. Furthermore, the diversity of DT applications—ranging from factory-floor automation to enterprise-level decision systems—makes it challenging to assess the state of knowledge comprehensively. There is also a paucity of systematic reviews or bibliometric mappings that chart the trajectory of research advancements, thematic clusters, and influential contributors within this domain. This fragmentation hinders scholars, practitioners, and policymakers from gaining a holistic understanding of the field's development and potential directions. Therefore, this study aims to provide a comprehensive bibliometric analysis of scholarly contributions on Digital Twin technology in the context of smart manufacturing.

2. LITERATURE REVIEW

2.1. *Conceptual Frameworks and Definitions*

The foundation of DT literature lies in understanding its core definition and structural components. The term "Digital Twin" was first popularized by [9] in the context of product lifecycle management, describing a virtual replica of a physical entity that maintains a real-time, bidirectional connection with its physical counterpart. [10] expanded this concept to encompass five essential elements: physical entity, virtual entity, services, data, and the connection mechanism. A comprehensive DT framework typically includes data acquisition systems (e.g., sensors), computational models (e.g., finite element models or AI-based simulators), and real-time communication infrastructure. More recent efforts, such as [11], have sought to categorize DTs into three levels: digital models (offline), digital shadows (real-time data without feedback), and digital twins (bi-directional synchronization). This taxonomy highlights the gradation in digital representations and serves as a benchmark for assessing technological maturity. These frameworks are essential for distinguishing DTs from related technologies like digital simulations and virtual prototypes.

2.2. *Enabling Technologies*

The implementation of DTs relies on a convergence of technologies that enable real-time data collection, processing, and actuation. IoT is a key enabler, providing the sensing infrastructure required to capture real-world parameters such as temperature, vibration, and pressure [12]. Cloud and edge computing platforms facilitate the storage and computation of massive data streams, while AI and machine learning (ML) algorithms support predictive modeling and anomaly detection. Additionally, simulation tools such as MATLAB Simulink, ANSYS, and Unity3D are commonly used to construct virtual models that emulate physical behaviors [13]. For instance, AI-driven DTs can learn from sensor data to optimize machine settings or production schedules. Blockchain has also emerged in the literature as a potential enabler for enhancing the trust, traceability, and security of data exchanged between physical and digital entities [14].

2.3. *Integration with Industry 4.0 Systems*

Digital Twin technology is increasingly viewed as a cornerstone of the industry 4.0 ecosystem. It complements and enhances other smart manufacturing technologies such as cyber-physical systems (CPS), robotics, additive manufacturing, and big data analytics [15]. Integration frameworks proposed by researchers often incorporate DTs as a middleware layer that bridges the gap between enterprise resource planning (ERP) systems and operational technology (OT) on the factory floor. In their integrated architecture, [16] proposed a Digital Twin Shop-Floor (DTS) model, in which each production asset is mapped by a twin to provide real-time insights for dynamic scheduling and quality assurance. Similarly, [17] outlined a reference model for DT integration, emphasizing interoperability, modularity, and scalability. Such integration allows for a holistic representation of manufacturing operations and supports agile decision-making in volatile environments.

2.4. *Applications in Smart Manufacturing*

The practical application of DTs in smart manufacturing is well-documented, with use cases ranging from design optimization to real-time process control. Predictive maintenance is among the most widely studied applications. By continuously monitoring machine conditions and analyzing historical performance data, DTs can anticipate equipment failures and recommend proactive maintenance strategies [18]. This reduces downtime, extends asset life, and minimizes operational costs. Another prominent application is digital production planning. Digital Twins enable simulation-based optimization of production layouts, workflows, and resource allocations without disrupting physical operations [19]. In quality control, DTs can detect anomalies in production processes and suggest corrective actions by comparing real-time data against virtual benchmarks. There is also growing interest in using DTs to personalize manufacturing outcomes, especially in high-mix, low-volume production settings such as the automotive and aerospace industries [20]. Moreover, DTs are being integrated into human-centric applications, such as worker training through augmented reality and digital ergonomics. These implementations create a feedback loop between human performance and machine behavior, fostering collaborative intelligence on the factory floor.

3. METHOD

This study employs a bibliometric analysis to explore the research advancements in Digital Twin (DT) technology within the context of smart manufacturing. The data were retrieved exclusively from the Scopus database, selected for its comprehensive coverage of peer-reviewed literature across disciplines relevant to engineering, computer science, and industrial technologies. The search was conducted using the keywords "digital twin" AND "smart manufacturing" within titles, abstracts, and keywords, with a publication year range limited to 2018–2024 to capture recent developments. The exported data included full bibliographic records, citations, authorship, and publication sources in .csv format, which were then analyzed using VOSviewer to perform co-authorship, co-citation, keyword co-occurrence, and bibliographic coupling analyses.

4. RESULTS AND DISCUSSION

4.1. *Results*

a. Descriptive Graph

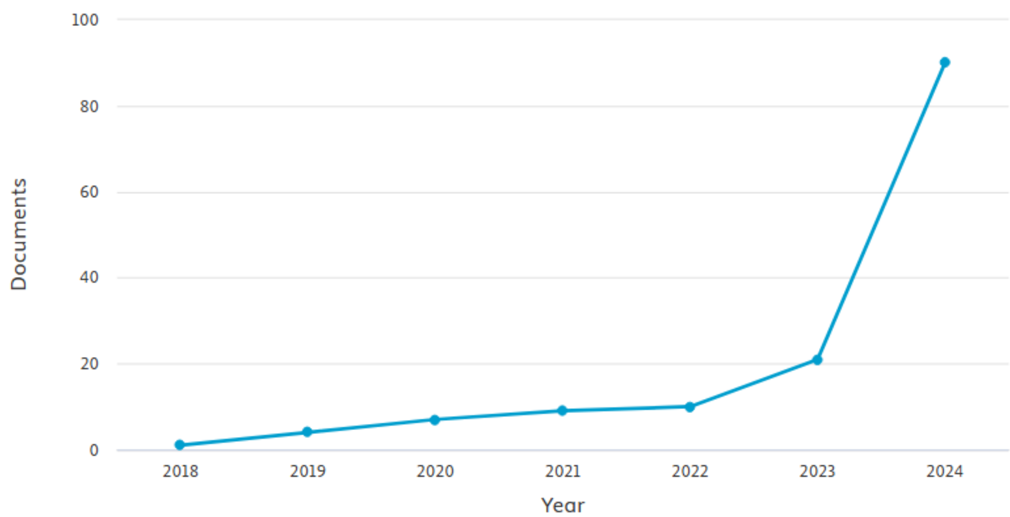

Figure 1. Documents by Year
Source: Scopus Database, 2025

The graph illustrates the annual growth in the number of research publications on Digital Twin technology in smart manufacturing from 2018 to 2024. The data reveal a clear upward trend, starting with minimal activity in 2018, followed by a steady but gradual increase from 2019 to 2022. Notably, there is a moderate rise in 2023, reaching approximately 20 documents, but a sharp and unprecedented surge occurs in 2024, with publications nearing 90 documents. This dramatic rise indicates a significant acceleration in scholarly interest and research output in this domain, possibly driven by the maturation of Industry 4.0 technologies and increased industrial adoption of Digital Twin systems. The spike in 2024 also suggests that Digital Twin has transitioned from an emerging concept to a central focus in smart manufacturing research.

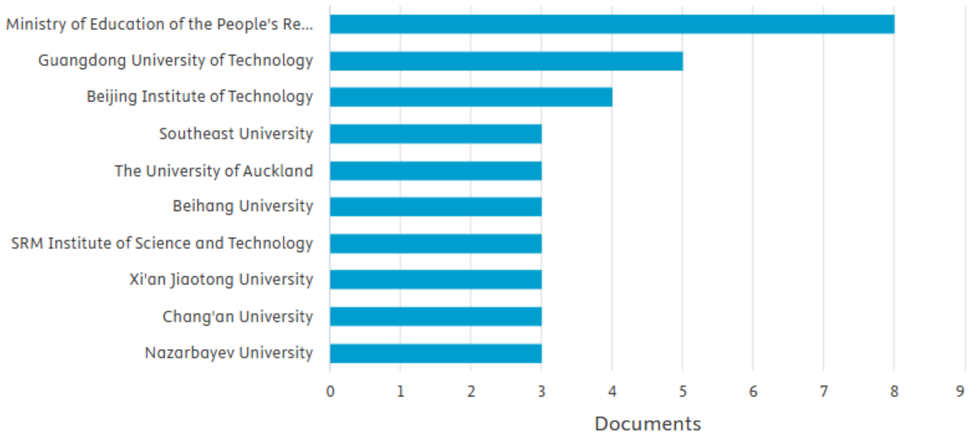

Figure 2. Documents by Affiliation
Source: Scopus Database, 2025

The chart displays the top contributing institutions in the field of Digital Twin research for smart manufacturing, ranked by the number of published documents. The Ministry of Education of the People's Republic of China leads significantly with 8 documents, indicating strong national support and policy-driven research initiatives. It is followed by the Guangdong University of Technology and the Beijing Institute of Technology, each contributing 5 and 4 documents respectively. A cluster of institutions—including Southeast University, The University of Auckland, Beihang University, SRM Institute of Science and Technology, Xi'an Jiaotong University, Chang'an University, and Nazarbayev University—each produced 3 publications, reflecting a globally distributed yet predominantly Asia-centric research landscape. The dominance of Chinese institutions highlights China's strategic focus and investment in smart manufacturing technologies, while the presence of universities from New Zealand, India, and Kazakhstan demonstrates the growing international interest and collaboration in advancing Digital Twin applications.

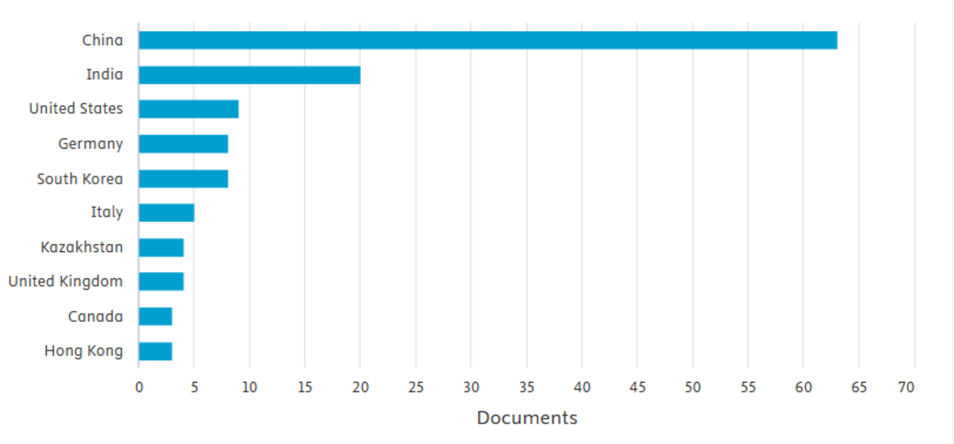

Figure 3. Documents by Country
Source: Scopus Database, 2025

The chart presents the distribution of research publications on Digital Twin technology for smart manufacturing by country. China dominates the field with an overwhelming lead of nearly 70 documents, underscoring its significant national emphasis on smart manufacturing and digital innovation. India follows at a distant second with around 20 documents, indicating a strong but comparatively smaller research footprint. Other countries such as the United States, Germany, and South Korea each contribute a moderate number of publications (approximately 8–10 documents), reflecting their established roles in industrial digitalization. European contributors such as Italy and the United Kingdom, along with Kazakhstan, Canada, and Hong Kong, have a modest presence in the dataset. This geographical distribution highlights the global nature of interest in Digital Twin technology, while also revealing a concentration of research activity in Asia, particularly led by China, which is rapidly positioning itself as a leader in the development and deployment of smart manufacturing technologies.

b. Citation Analysis

Table 1. Most Cited Article

Citations	Author and Year	Title
2060	[21]	Digital Twin in Industry: State-of-the-Art
1984	[22]	Digital twin-driven product design, manufacturing and service with big data
1089	[23]	Digital Twin: Enabling Technologies, Challenges and Open Research
1061	[24]	Review of digital twin about concepts, technologies, and industrial applications
1001	[25]	Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison
963	[26]	Digital Twin: Values, Challenges and Enablers From a Modeling Perspective
937	[27]	Material-structure-performance integrated laser-metal additive manufacturing
889	[28]	Enabling technologies and tools for digital twin
853	[29]	Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing
828	[30]	Digital twin-driven product design framework

Source: Scopus, 2025

c. Keyword Co-Occurrence Network Visualization

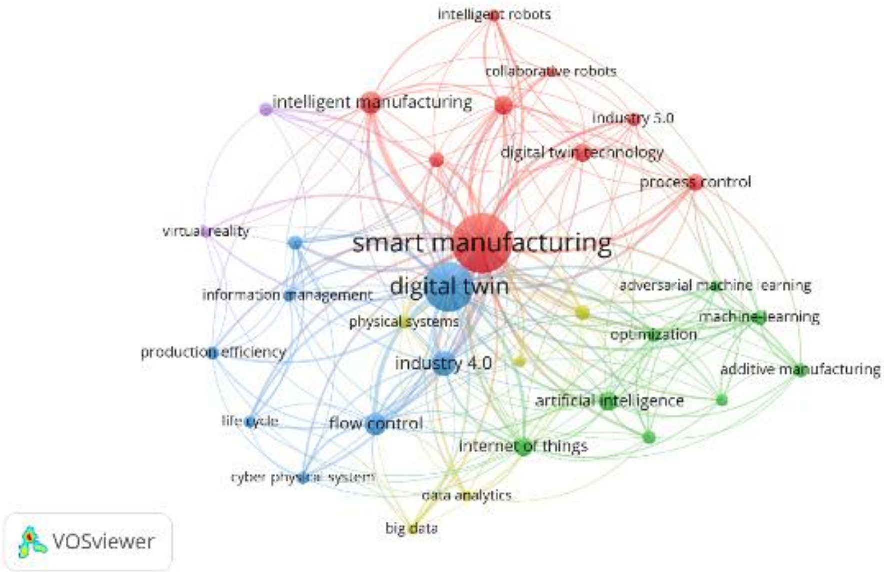

Figure 4. Network Visualization
Source: Data Analysis, 2025

The network visualization map illustrates the keyword co-occurrence analysis for scholarly publications related to Digital Twin technology in smart manufacturing. The map reveals a clustered structure of interconnected keywords, indicating the thematic landscape of this research domain. The most prominent and centrally located terms are “smart manufacturing” and “digital twin”, signifying their role as core concepts. These central nodes act as hubs that link various thematic clusters, reflecting their multidisciplinary nature and foundational position in the discourse. The size of the nodes represents the frequency of keyword occurrence, while the thickness of the connecting lines (links) signifies the strength of co-occurrence relationships.

The blue cluster, which is tightly linked to the central nodes, includes keywords such as “industry 4.0”, “flow control”, “cyber-physical system”, and “life cycle”. This grouping reflects the technological and systems-engineering foundation of Digital Twin applications. These terms emphasize the integration of DTs into the broader Industry 4.0 paradigm, particularly in the areas of system monitoring, lifecycle management, and operational optimization. The strong interconnections within this cluster suggest a well-established body of research addressing the infrastructure and control systems essential for implementing digital twins in smart factories.

The green cluster encompasses concepts like “machine learning”, “artificial intelligence”, “optimization”, and “additive manufacturing”. This group indicates a strong trend toward the AI-driven evolution of Digital Twins, where data-driven techniques are leveraged to enhance simulation accuracy, predictive capabilities, and autonomous decision-making. The presence of terms like “data analytics”, “big data”, and “internet of things” further highlights the reliance on real-time, large-scale data streams to fuel intelligent DT models. These connections underscore the symbiotic relationship between AI and Digital Twin technologies in advancing adaptive, self-optimizing manufacturing systems. The red cluster includes keywords such as “intelligent robots”, “collaborative robots”, “process control”, and “industry 5.0”. This indicates a thematic orientation toward human-machine collaboration and next-generation automation. The linkage to “digital twin technology” and “smart manufacturing” within this cluster reflects how DTs are being positioned as enablers of more responsive and collaborative industrial ecosystems, especially in the context of Industry 5.0, which emphasizes personalization, sustainability, and human-centric automation.

A purple cluster featuring terms like “intelligent manufacturing” and “virtual reality” suggests emerging intersections with immersive technologies and cognitive systems. This area of research is likely exploring how virtual representations—enabled by Digital Twins—can enhance decision support, remote monitoring, and operator training. The presence of “information management” and “production efficiency” implies a growing interest in how DTs can be applied not only in physical operations but also in strategic and managerial functions, supporting smarter and more integrated manufacturing enterprises.

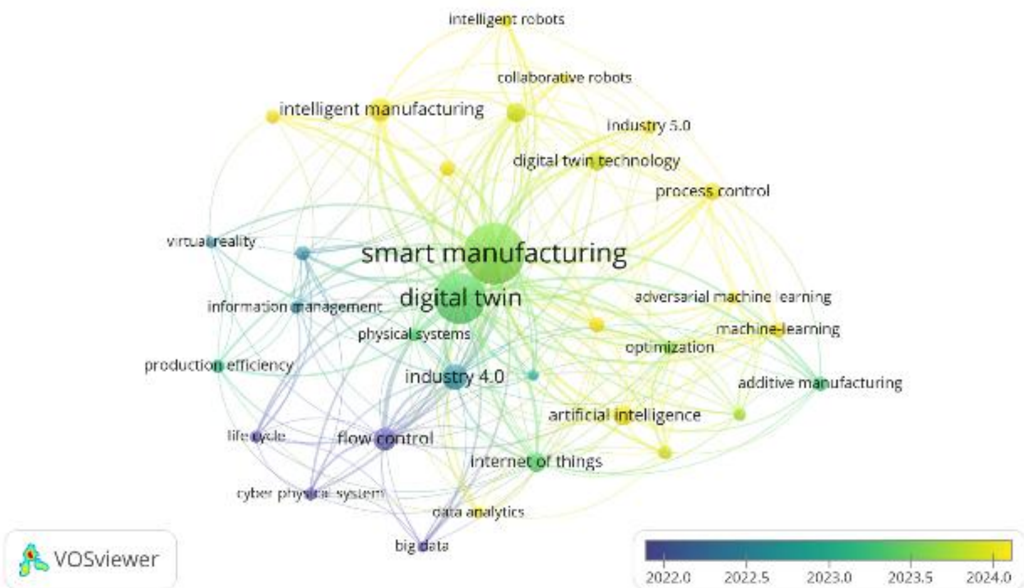

Figure 5. Overlay Visualization
Source: Data Analysis, 2025

The overlay visualization map generated by VOSviewer illustrates the temporal evolution of keywords in Digital Twin research for smart manufacturing from 2022 to 2024. The color gradient represents the average publication year associated with each keyword—blue and purple tones indicate earlier studies (closer to 2022), while yellow and green tones denote more recent research trends (closer to 2024). Core concepts like “smart manufacturing,” “digital twin,” and “industry 4.0” appear in green, signifying their sustained relevance and consistent appearance across the timeframe. These keywords remain central to the field, highlighting their continued foundational role in shaping research trajectories.

Emerging research directions are marked by yellow-colored keywords, which suggest increasing scholarly attention in the most recent year (2024). These include “intelligent robots,” “collaborative robots,” “adversarial machine learning,” “industry 5.0,” and “digital twin technology”, indicating a shift toward more advanced, AI-driven, and human-centric themes. Notably, terms like “additive manufacturing” and “optimization” are also colored in yellow, reflecting the field’s current emphasis on integrating Digital Twins into adaptive and efficient production strategies. These topics suggest a growing focus on next-generation manufacturing paradigms that blend intelligent automation, customization, and collaborative robotics. In contrast, blue and purple keywords such as “flow control,” “life cycle,” “production efficiency,” “cyber physical system,” and “information management” reflect earlier research interests, which concentrated more on systems engineering, data structures, and control mechanisms. While still relevant, these topics appear to be maturing or transitioning into foundational knowledge as attention moves toward newer applications and integration methods. This temporal mapping provides valuable insight into how the field is evolving—from early explorations of infrastructure and integration to current priorities involving AI, robotics, and Industry 5.0, signaling an increasingly sophisticated and interdisciplinary research landscape.

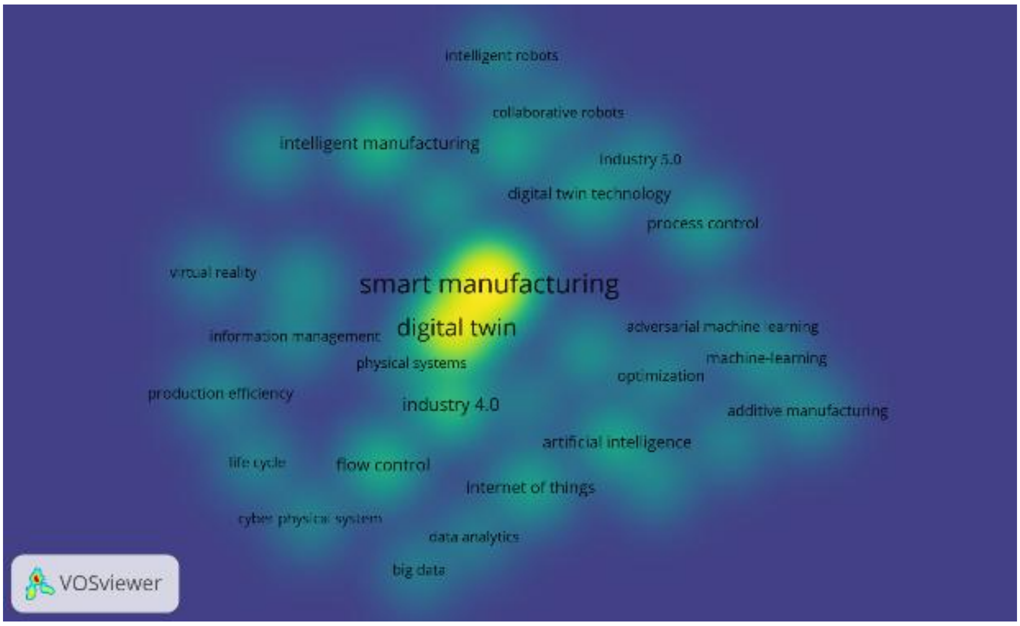

Figure 6. Density Visualization
Source: Data Analysis, 2025

The heatmap visualization illustrates the density of keyword occurrences in scholarly literature on Digital Twin technology for smart manufacturing. The intensity of the color—from dark blue (low frequency) to bright yellow (high frequency)—reflects how often specific keywords appear in the dataset. At the center of the map, “smart manufacturing” and “digital twin” are displayed in bright yellow, indicating their high frequency and centrality in the research landscape. These terms represent the core focus of the field and are frequently comentioned with numerous surrounding keywords, establishing them as foundational to current academic discourse. Surrounding these central themes, keywords such as "industry 4.0," "internet of things," "artificial intelligence," "flow control," and "intelligent manufacturing" appear in green and light blue, reflecting moderate to high relevance and frequency. Meanwhile, peripheral terms like "virtual reality," "adversarial machine learning," and "big data" are located in cooler blue areas, signifying lower but emerging attention in the literature. This distribution suggests that while the core focus remains on enabling smart and interconnected manufacturing via digital twin systems, newer, niche topics are gradually gaining traction and may shape future research directions.

d. Co-Authorship Network Visualization

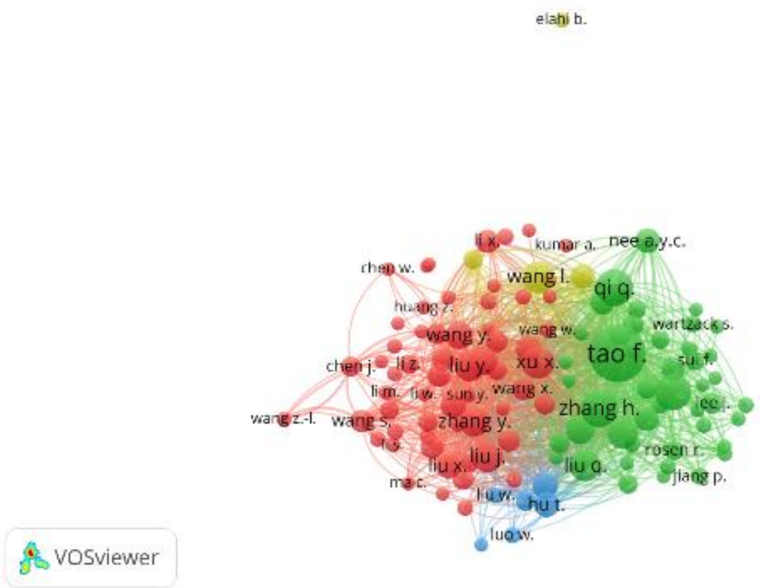

Figure 7. Author Visualization
Source: Data Analysis, 2025

The co-authorship network visualization illustrates the collaborative structure among prolific researchers in the field of Digital Twin technology for smart manufacturing. The nodes represent individual authors, with larger nodes indicating a higher number of publications or centrality in the network, while the connecting lines (edges) reflect co-authorship relationships. The visualization reveals several densely connected clusters, notably those surrounding key authors such as Tao F., Qi Q., Zhang H., Liu Y., and Xu X., who are prominent figures in the green cluster. These scholars are central to the field and exhibit strong collaborative ties with one another. The red and blue clusters represent other active research groups, also dominated by East Asian authors, particularly from China, highlighting the regional concentration of research output. Notably, a few isolated or weakly connected authors—such as Elahi B.—appear at the periphery, indicating either emerging researchers or those working independently

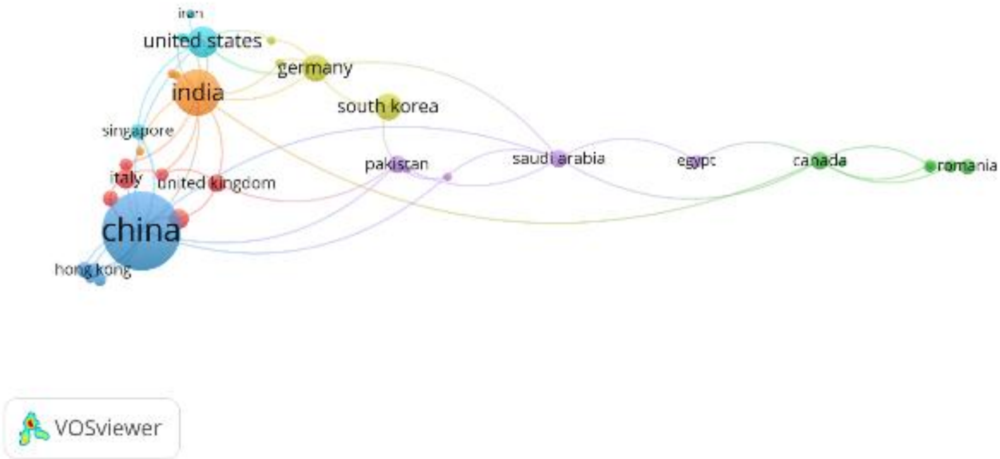

Figure 8. Country Visualization
Source: Data Analysis, 2025

The country collaboration network highlights the international research partnerships in the domain of Digital Twin technology for smart manufacturing. China emerges as the most dominant and central node, indicating its leading role and extensive collaboration network, especially with countries such as the United States, India, United Kingdom, and Italy. India also appears as a major hub, closely linked to several countries including Germany, Iran, and Singapore, reflecting its active engagement in global research efforts. The presence of clusters extending toward countries like Saudi Arabia, Egypt, Canada, and Romania suggests the formation of regional research alliances that connect Asia, the Middle East, and parts of Europe and North America. The visualization demonstrates that while China and India are the primary drivers of research output, there is a growing web of cross-border collaboration that enhances knowledge transfer and innovation capacity across the global academic community.

4.2. *Discussion*

a. Accelerated Growth and Maturity of Research

The publication trend from 2018 to 2024 reveals an exponential increase in scholarly output, particularly with a significant spike in 2024. This growth aligns with the broader advancement and adoption of Industry 4.0 technologies, where digital twin systems serve as a core enabler. The surge in 2024 likely reflects both the technological readiness and the urgency for resilient, flexible manufacturing solutions in a post-pandemic industrial landscape. As industries seek to digitally simulate and optimize their operations, academia has responded with increased empirical, theoretical, and methodological research, solidifying DTs as a mature and central topic in smart manufacturing discourse.

b. Institutional and Country-Level Dominance

Analysis of the most productive institutions highlights the dominant role of Chinese universities and government agencies. The Ministry of Education of the People’s Republic of China and universities such as Guangdong University of Technology and Beijing Institute of Technology are at the forefront of DT research. This strong representation is echoed in the country-level data, where China leads overwhelmingly with nearly 70 publications, followed distantly by India and the United States. These figures reveal China's strategic prioritization of smart manufacturing in its national research agenda, supported by government funding, industrial policy, and innovation ecosystems. India's rising contribution—closely linked with partnerships in the US, Germany, and the UK—signals its growing stake in digital industrial transformation. Meanwhile, countries like Germany, South Korea, Italy, and Canada continue to play notable roles, although their output is relatively modest. Emerging participation from countries such as Saudi Arabia, Egypt, Romania, and Kazakhstan suggests a widening global interest, potentially driven by regional policy shifts and academic collaborations with more established research hubs.

c. Thematic Focus and Knowledge Structure

Keyword co-occurrence analysis reveals that "smart manufacturing" and "digital twin" are not only the most frequent terms but also serve as central nodes in the conceptual structure of the field. These terms are deeply interconnected with adjacent technologies such as "industry 4.0," "cyber-physical systems," "flow control," and "lifecycle management." This indicates a strong alignment with digital transformation frameworks aimed at operational efficiency, system integration, and real-time decision-making. Notably, the presence of keywords like "artificial intelligence," "internet of things," "data analytics," and "machine learning" in high-density clusters reflects the growing influence of data-driven intelligence in enhancing the capabilities of digital twins. These technologies enable more accurate modeling, autonomous control, and predictive maintenance, marking a shift from static digital representations to dynamic, self-optimizing systems. This convergence of DT and AI is a defining feature of next-generation smart factories. Further, the emergence of "collaborative robots," "intelligent robots," and "industry 5.0" in recent years—as shown in the overlay visualization—signals a transition toward human-centric and hybrid automation paradigms. Industry 5.0 emphasizes collaboration between humans and machines, customization, and sustainability. The integration of DT with robotic systems and immersive technologies like virtual reality further expands the application scope into areas such as remote operations, ergonomic analysis, and augmented training.

d. Temporal Evolution of Research Themes

The overlay map analysis suggests that while core themes like digital twin, smart manufacturing, and industry 4.0 remain stable, newer areas such as "adversarial machine learning," "optimization," "digital twin technology," and "intelligent manufacturing" are gaining traction. These themes are colored yellow and green, indicating recent average publication years (closer to 2024). This trend reflects an evolving focus toward advanced computational models, security concerns in AI-integrated systems, and scalable optimization of manufacturing processes. The temporal gradient also reveals a shift in priorities—from foundational concerns like flow control, lifecycle, and information management in earlier years, toward flexibility, autonomy, and intelligence in the most recent studies. This suggests that researchers have moved beyond establishing the feasibility of DTs and are now refining their functionality, interoperability, and real-world deployment.

e. Collaboration Patterns and Scholarly Influence

The co-authorship network highlights influential scholars such as Tao F., Qi Q., Zhang H., and Xu X., who serve as intellectual anchors within the field. These authors are not only prolific but also highly connected, indicating strong collaborative linkages and possibly the presence of academic clusters or schools of thought. Their frequent co-authorships suggest shared research agendas, particularly in the Chinese research ecosystem, supported by institutional alliances and national research funding. The international collaboration map further reinforces this insight, with China and India forming extensive bilateral and multilateral partnerships, particularly with the United States, Germany, and the United Kingdom. These relationships are essential in driving global knowledge exchange and enhancing the scientific rigor of DT research. Cross-country linkages with Saudi Arabia, Canada, Egypt, and Romania also demonstrate the diversification of the research community and its movement toward global inclusivity, with developing countries increasingly contributing to and benefiting from smart manufacturing innovations.

f. Research Gaps and Future Directions

Despite the substantial growth, several gaps persist. First, much of the literature is technology-centric, often focusing on system design, simulation, and modeling. There is a relative paucity of empirical studies examining DT adoption in real industrial settings, including organizational, human, and regulatory dimensions. Understanding the socio-technical challenges of implementation is crucial for successful deployment. Second, while AI integration is prominent, ethical concerns and cybersecurity issues related to digital twins remain underexplored. As DTs become increasingly autonomous and data-rich, the risks of bias, algorithmic opacity, and data breaches warrant more attention. Future studies should investigate frameworks for explainable DTs, secure data sharing, and privacy-preserving architectures. Third, there is a need to develop standardized frameworks and evaluation metrics to assess the performance, scalability, and return on investment (ROI) of DT deployments across sectors. Comparative case studies, longitudinal analyses, and industry-academic collaboration will be essential in addressing these gaps.

5. CONCLUSION

This bibliometric study provides a comprehensive overview of the evolving landscape of Digital Twin (DT) technology within the context of smart manufacturing, highlighting its rapid growth, dominant contributors, and shifting thematic focus. The analysis reveals that research on DT has accelerated significantly in recent years, with China and India emerging as leading contributors both institutionally and nationally. Central themes such as "smart manufacturing," "digital twin," and "industry 4.0" remain foundational, while recent attention has shifted toward advanced topics like artificial intelligence, collaborative robotics, and Industry 5.0. The collaboration networks among authors and countries illustrate a highly interconnected global research ecosystem, albeit with notable concentration in Asia. Despite the growing body of literature, gaps remain in empirical application, standardization, and the socio-ethical dimensions of DT implementation. As the field matures, future research must not only enhance technical sophistication but also address practical, ethical, and organizational challenges to ensure that digital twin technologies are effectively and sustainably integrated into the smart factories of the future.

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