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Research Article

Bibliometric Review of Smart Factory Transformation in Managerial Perspective

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ABSTRACT

This study synthesizes the global research on smart factory transformation from a managerial perspective by examining publication trends, thematic clusters, and content structures across four categories: transformation impacts, influencing factors, barriers and maturity models. A mixed-method literature review was employed, combining bibliometric analysis with qualitative content analysis in accordance with PRISMA guidelines. A comprehensive search of the Scopus database identified 154 English studies published between 2015 and 2024 that address managerial aspects of smart factory transformation. Results show a rapidly expanding scholarly interest, peaking at 34 publications in 2024. Research activities are concentrated in Asia, North America, and Europe, with China and India emerging as dominant contributors. Despite increasing volume, the content analysis reveals highly fragmented knowledge, particularly concerning the prioritization of managerial decisions, sequencing of transformation activities, and integration of strategic, technological and organizational dimensions. For practitioners and policymakers, the findings underscore the need for a holistic, goal-oriented framework to support transformation governance.

Keywords: Bibliometric Review, Managerial Perspective, Smart Factory, Transformation.

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INTRODUCTION

The Fourth Industrial Revolution, launched in 2011, has opened a new era for traditional manufacturing. Conventional production systems are becoming increasingly intelligent through the integration of Industry 4.0 technologies (Hozdić, 2015; Wan *et al*., 2019; Xu and Hua, 2017). This shift is characterized by real-time monitoring, autonomous decision-making, and adaptive production capabilities. A primary achievement of this revolution is the emergence of smart factories, which feature a fully connected manufacturing system, mainly operating without human force by generating, transferring, receiving and processing the necessary data to conduct all required tasks for producing all kinds of goods (Osterrieder *et al*., 2020). However, the transition toward the smart factory requires not only technological, process, and resource transformations (Jung *et al*., 2023; Sjödin *et al*., 2018), but also a comprehensive roadmap that involves assessing the current level of readiness, formulating an appropriate strategy, and establishing an effective governance model to ensure optimal transformation outcomes (Dreyer *et al*., 2022; Jo, 2023; Kahveci *et al*., 2022; Shi *et al*., 2020).

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In the context of the smart factory, the transformation is not a simple technological upgrade but a systemic reconfiguration of production, workforce, and business models (Ghobakhloo, 2018; Kamble *et al*., 2020). Managing this process requires a governance perspective that moves beyond purely technical considerations to address broader organizational and strategic challenges (Mittal *et al*., 2020; Sjödin *et al*., 2018). The impact of transformation must be assessed to understand how smart factory adoption translates into performance, productivity, competitiveness, and sustainability (Büchi *et al*., 2020). Identifying the influence factors such as leadership, digital capabilities, supply chain integration, and institutional support, is critical for enabling successful transformation (Ghobakhloo and Ching, 2019; Sjödin *et al*., 2018). Analyzing barriers and challenges helps managers anticipate and mitigate risks, including cost pressures, interoperability issues, skills shortages, and cybersecurity threats (Shi *et al*., 2020; Wang *et al*., 2022). The use of readiness criteria and maturity models provides structured frameworks to assess current capabilities, benchmark progress, and design sequenced roadmaps for implementation (Mittal *et al*., 2020; Schumacher *et al*., 2016).

Over the past decade, numerous studies have made meaningful contributions toward realizing the smart factory from diverse perspectives. Nevertheless, this diversity has led to fragmented knowledge, making it difficult to identify the core aspects critical for successful implementation (Bagherian and Mukherjee, 2025). To address these issues, we employed bibliometric and content analysis methodologies, utilizing the Scopus database to enhance the accuracy and depth of our study. This review also adopts the Technology-Organization-Environment (TOE) framework to systematically categorize influencing factors and barriers, and the lens of Dynamic Capabilities (DC), thereby providing a theoretically grounded and holistic perspective on the management of smart factory transformation. The following sections present some related works, describe in detail the methodology, the results of bibliometric analysis and content analysis, the discussion including future directions and the conclusion.

SMART FACTORY TRANSFORMATION LITERATURE REVIEWS

Recent review studies have approached the transition toward smart manufacturing and smart factories from multiple thematic angles.

Regarding the impact of transformation, Krishnan (2024) shows that existing literature predominantly examines how firms leverage smart manufacturing to achieve sustainability goals, implement lean and green practices, and enhance diagnostics and maintenance capabilities. However, the author emphasizes that the field still lacks an integrated synthesis of transformation benefits that would sufficiently motivate SMEs to adopt smart technologies. Similarly, Tiwari *et al*. (2023) extend the discussion of impacts by mapping how Industry 4.0 contributes to sustainable supply chains, digital-sustainability interlinkages, and the circular economy, thereby filling gaps left by earlier fragmented reviews.

In terms of influencing factors, studies situated within the industry 4.0, Industry 5.0 discourse highlight the growing role of human-centric, resilience-oriented, and sustainability-driven considerations. For example, Lei *et al*. (2024); Zhang *et al*. (2023) clarify how enabling factors, such as human-machine collaboration, skill development, and responsible technology deployment, shape the evolution from a technology-driven Industry 4.0 paradigm to a people-focused Industry 5.0 perspective. Their work outlines technological, organizational, and social factors that support next generation smart manufacturing.

Research on barriers and challenges is synthesized extensively in Valipour *et al*. (2024), who systematically classify obstacles to smart manufacturing implementation and map them to stakeholder groups, including governments, firms, technology providers, workers, and customers. They further connect these barriers to core technological components such as IoT, AI, big data, robotics, cloud computing, and cybersecurity. Additional reviews, such as Sufian *et al*. (2021), complement this perspective by detailing common obstacles encountered by SMEs, high investment costs, skill shortages, limited standardization, and industry-specific constraints, and by proposing micro-strategies to help firms overcome these barriers.

A substantial body of literature also examines maturity and readiness for transformation. Vance *et al*. (2023) provide one of the most comprehensive syntheses of maturity models, covering both academic and consultancy-based frameworks. Their review highlights persistent gaps, notably the absence of SME-oriented maturity models and insufficient attention to governance, leadership, and cybersecurity readiness. Krishnan (2024) further contributes by offering a staged transformation framework to help SMEs leverage existing resources, initiate low-cost transitions, and scale toward advanced technological adoption. Napoleone *et al*. (2020) add to readiness assessment by distinguishing cyber-physical system characteristics linked to technological and operational management preparedness across organizational, human resource, training, and change processes.

Technology-focused review studies broaden the landscape by examining key digital components that enable smart factories. Soori *et al*. (2023) review IoT applications, identifying benefits in optimization, predictive maintenance, energy reduction, and supply chain efficiency, while acknowledging challenges related to cost and security. Gupta *et al*. (2022) survey the Industrial Internet of Things (IIoT), emphasizing both its opportunities for real-time monitoring and its constraints concerning interoperability and big data. del Real Torres *et al*. (2022) highlight the growing importance of Deep Reinforcement Learning in supporting manufacturing tasks through robotics, scheduling, maintenance, and digital twins, while Bahrpeyma and Reichelt (2022) synthesize the role of multi-agent reinforcement learning for factory control. Anumbe *et al*. (2022) expand this technological perspective through their analysis of Factory-of-the-Future architectures, emphasizing IT-OT integration across management, connectivity, control, and data layers.

Synthesizing insights across these categories reveals persistent knowledge fragmentation. Existing reviews have often focused narrowly on technological, sustainability, or opportunity, challenge perspectives while underemphasizing the managerial complexity of smart factory transformation (Tiwari *et al*., 2023; Valipour *et al*., 2024). As shown in the future research directions summarized in Table 1, Notable gaps remain in areas such as strategic transformation planning, capability development, technology-management integration, resilience building, and the establishment of standardized, secure, and human-centric transformation pathways. The authors recognize the need for a comprehensive review that simultaneously addresses the impacts, influencing factors, barriers, readiness models, and technological foundations of the transformation while maintaining a central focus on managerial processes. Therefore, the present paper responds to this gap by offering an integrated, management-oriented overview of the transformation foundations.

METHODOLOGY

This study adopts a systematic review approach that integrates bibliometric analysis and content analysis to examine the literature on smart factory transformation.

Bibliometric analysis offers powerful tools to map the intellectual structure, research hotspots, and emerging trends in this evolving field. By examining patterns in annual publication output, journal impact, document influence, and keyword co-occurrence, it is possible to identify dominant research themes, underexplored topics, and potential future directions (Jerman *et al.*, 2018).

Content analysis, originally defined by Berelson (1952) and later developed by Mayring (2000, 2014), was employed to complement the bibliometric mapping. A key advantage of content analysis is its ability to combine in-depth qualitative approaches with powerful quantitative analyses (Krippendorff, 2018; Mayring, 2014). This method enables flexible investigation on two levels: (1) the manifest content of texts and documents, and (2) the latent content and deeper meanings embodied in the texts.

Compared with traditional narrative reviews, a mix-method literature review offers greater objectivity in searching, screening, and analyzing publications (Snyder, 2019). Therefore, this study leverages the systematic review protocol and the content analysis method to classify, analyze, and synthesize the foci, methods, and indicators of smart factory transformation research, as well as their connections to the formal characteristics of the reviewed papers.

Data collection

The review process was guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards (Page *et al.*, 2021) to ensure transparency and replicability. The procedure consisted of four main stages:

(1) A two-layer keyword strategy was employed to capture research relevant to smart factory transformation. The first layer consisted of general terms (“smart factory” OR “intelligent factory” OR “digital factory” OR “autonomous factory” OR “factory of the future” OR “industry 4.0 factory” OR “smart factories” OR “intelligent factories” OR “digital factories” OR “autonomous factories” OR “factories of the future” OR “industry 4.0 factories” and “smart manufactur*” OR “intelligent manufactur*” OR “digital manufactur*” OR “advanced manufactur*”) in the title, while the second layer focused on the transformation dimension

Table 1: Related literature review research.

Thematic angles	References	Future directions
The impacts of transformation	Krishnan (2024); Tiwari *et al.* (2023)	New business models Sustainability frameworks Resilience and adaptability Operational management Integrating human factors
The influencing factors	Lei *et al.* (2024); Zhang *et al.* (2023)	Dynamic capability Collaboration Strategies for training and upskilling Policy and societal frameworks Supply chain integration Standardization Cost-benefit analysis
The barriers and challenges	Sufian *et al.* (2021); Valipour *et al.* (2024)	Data security and safety Communication technologies Integration (AI, Human-CPS) Experimental validation
The maturity and readiness	Krishnan (2024); Napoleone *et al.* (2020); Vance *et al.* (2023)	Maturity models (focus on SMEs, cybersecurity, governance) Standardization frameworks for IIoT
Technology	Anumbe *et al.* (2022); Bahrpeyma and Reichelt (2022); del Real Torres *et al.* (2022); Gupta *et al.* (2022); Soori *et al.* (2023)	AI/ML integrated with IoT, autonomous systems, and human-machine IIoT architectures based on edge and cloud

(transform* OR transit* OR adopt* OR implement* OR integrat* OR deploy* OR migrat* OR upgrade) in title, abstract, keyword.

(2) The Scopus database was used to search for and identify the relevant articles. Filters such as articles published only in English were applied. Articles published from 2015 to 2024 are included in the list. This process resulted in 987 articles.

(3) This list of 987 articles was downloaded, and 9 duplicates were removed, leaving 978 articles.

(4) We selected articles that address the transformation toward smart factories from a managerial perspective by screening titles and abstracts. Following prior reviews, we focused on studies that identify (i) the impacts, (ii) the factors influencing, (iii) the barriers and challenges and (iv) the maturity models or readiness assessments of smart factory transformation. The titles of these 978 articles were screened, resulting in the removal of 628 irrelevant studies. After reviewing the abstracts of the remaining 350 articles manually to ensure relevancy to the topic, smart factory/smart manufacturing transformation, then further led to the removal of an additional 196 articles. The final 154 articles were then considered for further analysis.

Data analysis

The data analysis was conducted in two main stages, combining bibliometric techniques and qualitative content analysis. The first stage focused on the descriptive and mapping characteristics of the dataset. Specifically, the reviewed articles were categorized by year of publication to identify temporal trends, and by country of origin to highlight geographical distribution of research activities. Journals and publishers were also examined, and their quality was assessed using the SCI mago Journal Rank indicator, which allows for a systematic evaluation of the academic outlets where research on smart factory transformation is disseminated. Influential studies were identified based on citation counts, and keyword co-occurrence were visualized through VOS viewer to reveal clusters of research themes and collaborative patterns. These steps provide a quantitative overview of the landscape and help to uncover structural relationships within the field.

In the second stage, a more detailed content analysis was performed to examine the managerial dimensions of smart factory transformation. Abstracts and, where relevant, full texts were coded and classified into thematic categories. This approach enables the identification of how managerial aspects are addressed across different studies, the scope of their applications, and the degree to which the literature connects technical transformation with organizational and managerial capabilities. By integrating bibliometric mapping with qualitative content analysis, this study captures both the broad research landscape and in-depth managerial insights, providing a robust foundation for identifying future research directions

RESULTS AND DISCUSSION

Analysis of year and countries of publication

A total of 154 publications on smart factory transformation were identified between 2015 and 2024. Table 2 presents the annual distribution of these studies, showing a steady upward trajectory over the past decade. The number of publications remained modest in the early years, with only three to four papers annually between 2015 and 2017, before accelerating noticeably from 2018 onwards. The trend culminated in a peak of 34 publications in 2024. This consistent growth highlights that, while the field is still in a formative stage, scholarly attention is rapidly expanding and the topic is gaining strong research momentum.

Country-wise analysis was performed to identify the countries having maximum contribution as corresponding authors to publish articles related to smart factory transformation. Table 2 also presents the top 10 most productive countries in this field. A total of 49 countries have contributed to the body of literature. As shown in the database of Scopus, research outputs are primarily concentrated in Asia, North America, and Europe. China and India lead as the world's primary manufacturing hubs, while the

Table 2: Number of articles related to smart factory transformation, by year and by country (Scopus, 26/8/2025).

Year	Documents	Country	Documents	Citations
2015	3	China	31	1664
2016	3	India	26	951
2017	4	United States	21	1460
2018	10	South Korea	20	415
2019	13	Italy	12	1043
2020	16	Germany	9	215
2021	24	Taiwan	7	375
2022	18	United Kingdom	6	504
2023	29	Malaysia	6	358
2024	34	France	5	386

United States and South Korea emerge as key contributors due to their advanced technological expertise The participation of various countries further enhances the geographical diversity of the research landscape. This wide global distribution demonstrates that the development of studies on smart factory transformation is not limited to a specific country or region but rather represents a shared global challenge and a collaborative scientific endeavor.

The overlay visualization map in Figure 1 illustrates the temporal evolution of international publications on smart factory transformation. As shown in the color gradient ranging from purple (2019) to yellow (2024). Early contributions primarily originated from countries such as Slovenia, Finland, Singapore... More recent publications (highlighted in yellow) are concentrated in emerging contributors such as Australia, Serbia, Azerbaijan… suggesting growing interest from a broader set of countries in recent years. This temporal shift demonstrates a clear global diffusion of research efforts, moving from early adopters in technologically advanced nations to a wider range of developing and industrializing countries. The progression indicates not only a sustained interest in the field but also an expanding global research network responding to the evolving challenges and opportunities of Industry 4.0.

Distribution of source journals

Analyzing the most influential journals within the research domain helps identify the core group of journals that are leading and shaping the direction of the field. Each journal tends to prioritize specific topics, which provides insights into the emerging and prominent research trends. Table 3 presents the top ten journals with the highest number of publications on the topic of smart factory transformation from 2015 to 2024. The columns respectively show the number of publications, the corresponding total citations, Impact Factors (IF) and the journal rankings according to the Scimago Journal Rank (SJR).

The top six journals with the highest number of publications over the past decade accounted for 36 articles, representing 23.4% of the total output (154). However, these journals collectively attracted 2,039 citations, which corresponds to 37% of all citations, underscoring their strong influence on the field. All six journals are ranked in Q1, highlighting their scholarly prestige. Particularly, Technological Forecasting and Social Change (IF=13.3) and the International Journal of Production Economics (IF=10) demonstrate high impact factors, suggesting that research published in these outlets is more likely to shape future academic discussions and provide theoretical foundations for subsequent studies.

A closer look reveals that these outlets can be broadly divided into two groups: specialized manufacturing journals (e.g., Journal of Manufacturing Technology Management, International Journal of Advanced Manufacturing Technology, International Journal of Computer Integrated Manufacturing) and interdisciplinary journals (e.g., Sustainability, Technological Forecasting and Social Change). While specialized outlets primarily focus on production technologies, operational practices, and industry-specific challenges, interdisciplinary outlets extend the debate toward broader themes such as sustainability, foresight, and societal implications. This distinction illustrates both the fragmentation and the richness of the field, showing that smart factory transformation is not only rooted in technical and operational

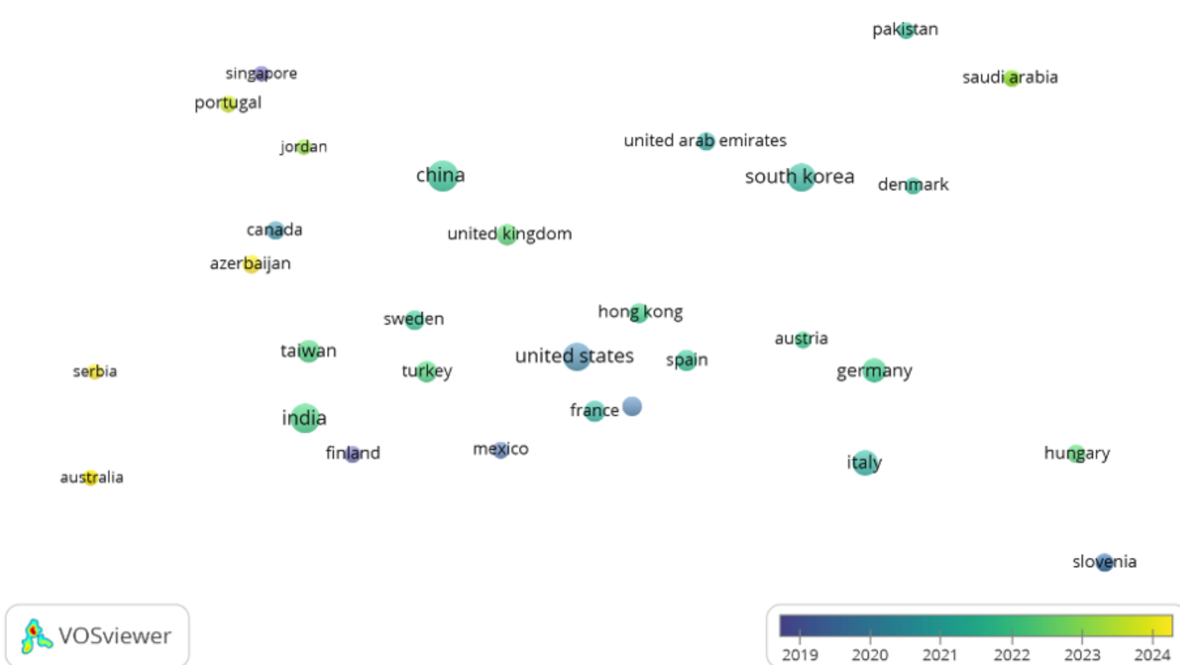

Figure 1: Overlay visualization map of the published literature in a country.

Table 3: Top journals in number of research (2015-2024).

Sl. No.	Journal	Count	Citation	IF	JCR	H-Index
1.	Journal of Manufacturing Technology Management	7	283	6	Q1	100
2.	International Journal of Computer Integrated Manufacturing	7	208	4.0	Q1	74
3.	Sustainability Switzerland	6	233	3.3	Q1	207
4.	International Journal of Advanced Manufacturing Technology	6	305	3.1	Q1	175
5.	Technological Forecasting and Social Change	5	685	13.3	Q1	209
6.	International Journal of Production Economics	5	595	10	Q1	148

Table 4: Top ten documents in number of total citation (2015-2024).

Sl. No.	Document	(i)	(ii)	(iii)	(iv)	TC
1.	Büchi *et al.* (2020)	✓				554
2.	Sjödin *et al.* (2018)	✓	✓	✓		381
3.	Ghobakhloo and Ching (2019)		✓	✓		306
4.	Kamble *et al.* (2020)	✓	✓			297
5.	Tao *et al.* (2017)	✓		✓		286
6.	Wang *et al.* (2022)		✓	✓		256
7.	Qu *et al.* (2019)	✓		✓		202
8.	Mittal *et al.* (2020)				✓	171
9.	Gillani *et al.* (2020)	✓	✓			167
10	Shi *et al.* (2020)		✓	✓		164

(i) impacts of transformation; (ii) influencing factors; (iii) barriers and challenges; (iv) maturity models and readiness assessments; TC: Total citation.

research but is also increasingly contextualized within wider organizational and societal frameworks.

The most influential study on smart factory transformation

The ten most-cited studies in Table 4 accumulate 44.5% of total citations, establishing the intellectual foundation across all four thematic areas.

To capture the intellectual structure of the most influential studies, a matrix was developed that maps the top 10 cited articles against four thematic categories: (i) impacts of smart factory transformation, (ii) influencing factors, (iii) barriers and challenges, and (iv) readiness and maturity models. This matrix reveals that most studies do not confine themselves to a single perspective but instead span multiple dimensions. The intellectual foundation mapped in Table 4 reflects a clear evolutionary trajectory in the scholarly discourse on smart factories.

(i) Early research efforts predominantly concentrated on the impacts of transformation, aiming to validate the strategic value and performance gains of intelligent systems. Adopting Industry 4.0 technologies enhances firm performance and productivity (Büchi *et al.*, 2020), creates value through digital servitization (Sjödin *et al.*, 2018), improves sustainability outcomes when combined with lean practices (Kamble *et al.*, 2020), and strengthens competitiveness through digitalization (Gillani et al., 2020). Similarly, Tao *et al.* (2017) and Qu *et al.* (2019) highlight efficiency and flexibility gains enabled by big data and smart manufacturing solutions. These align with the sensing phase in DC theory by focusing on identifying and evaluating the strategic opportunities and potential value created by digital adoption.

(ii) Over time, the focus shifted toward influencing factors and implementation barriers, representing a concerted scholarly effort to move from theoretical conceptualization to the practical realization of smart manufacturing. These include organizational capabilities and external collaboration (Sjödin *et al.*, 2018), managerial support and competitive pressure (Ghobakhloo and Ching, 2019), cultural alignment and leadership commitment (Gillani *et al.*, 2020; Kamble *et al.*, 2020), as well as human-centric dimensions such as skills and ergonomics (Wang *et al.*, 2022); Shi *et al*. (2020) further underline technology, strategy, and people as interdependent drivers of adoption.

(iii) Barriers and challenges: Common issues include high investment costs and lack of expertise (Ghobakhloo and Ching, 2019; Shi *et al*., 2020), integration and interoperability problems (Qu *et al*., 2019; Tao *et al*., 2017), and workforce skill gaps or misalignment between humans and machines (B. Wang *et al*., 2022). Resource constraints are also found to limit SMEs' ability to implement digital servitization (Sjödin *et al*., 2018). Following DC theory, seizing capability involves shifting the focus toward mobilizing resources, addressing constraints, and establishing the necessary conditions to capture technological value.

(iv) However, Table 4 also reveals a critical imbalance: only one of the top ten influential studies explicitly addresses maturity model. Mittal *et al*. (2020) provide a systematic review of maturity models, offering SMEs structured pathways for assessing and guiding their digital transformation journey. This is the transforming stage in DC theory. This stage centers on the systematic reconfiguration of organizational structures and continuous alignment to achieve long-term digital maturity and sustained competitiveness. The lack of studies on maturity model highlights a persistent gap in the literature, where managerially-oriented frameworks for structured digital progression remain significantly limited compared to performance-driven or factor-based analyses.

Overall, the matrix reveals that smart factory transformation requires a holistic perspective integrating drivers, constraints, and maturity pathways. Notably, the 10 most influential works, comprising 44.5% of total citations, function as foundational anchors bridging technological and managerial dimensions across thematic clusters.

Co-occurrence analysis of authors' keywords

Figure 2 presents the keyword co-occurrence visualization of the smart manufacturing literature from 2015 to 2024, generated using VOSviewer. Co-occurrence analysis highlights which keywords are commonly studied together, helping to define major thematic clusters within the field. The result of co-occurrence analysis shows nine clusters with total 70 keywords that appeared at least three times across the dataset.

The centre keywords of Cluster 1 (Red) "smart manufacturing", Cluster 2 (Green) "manufacture", Cluster 3 (Blue) "industry 4.0", Cluster 4 (Yellow) "digital manufacturing", Cluster 5 (Purple) "intelligent manufacturing", Cluster 6 (Cyan) "industrial revolution" and Cluster 7 (Orange) "smart factory": Taken together, these clusters represent a broad spectrum of research perspectives on the transition such as technological dimension, strategic and managerial aspects, "critical success factors", "readiness assessment", "maturity model", impacts and sustainability, human and organization oriented dimensions.

Cluster 8 (Brown): This cluster centers on production processes and technical implementation, with a strong focus on "flow control", "internet of things", "embedded systems", "manufacturing process", and "requirements". It reflects research attention to the operational and system-level aspects of enabling transformation.

Cluster 9 (Pink): This cluster highlights sustainability and human-centered development. Keywords such as "sustainability", "personnel training", "human resource management", "managers" and "hierarchical systems" illustrate the growing concern for aligning technological transformation with human development, workforce capabilities, and organizational structures.

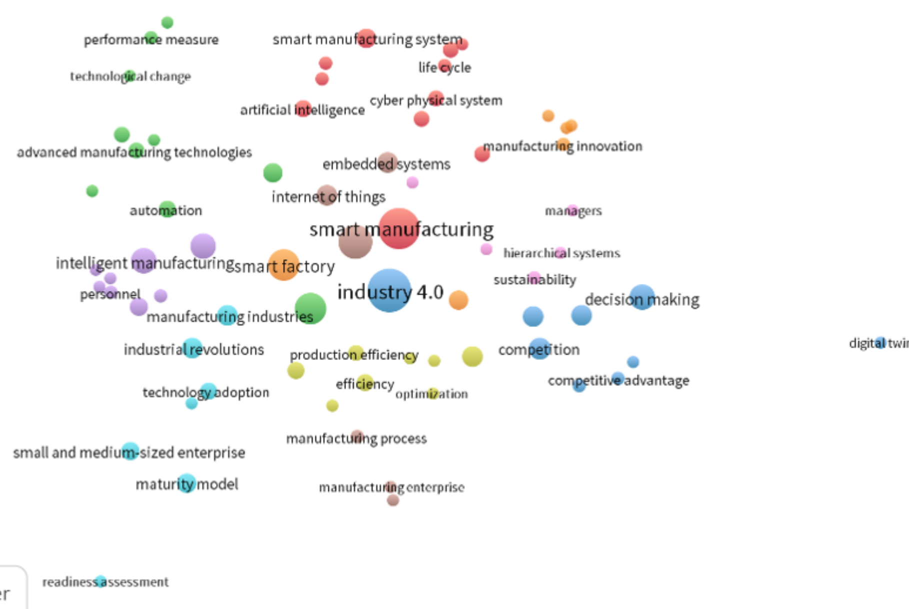

Figure 2: Keyword co-occurrence visualization.

Figure 3: Keyword co-occurrence overlay visualization.

Figure 3 presents the keyword co-occurrence overlay visualization of the smart manufacturing literature from 2015 to 2024. The color gradient, ranging from purple (earlier years) to yellow (more recent years), shows the temporal evolution of research topics. Early studies (2019-2020) emphasized foundational technological aspects such as "automation" and "digital technologies" or "standardization", "government". From 2021 onward, attention gradually shifted toward managerial dimensions and sustainability-oriented theme, including "maturity model", "life cycle", "environmental impact", "sustainability". More recent studies (2022-2023) highlight and human-centered themes, with keywords such as "human capital" and "personnel training". Recent researchs have also focused on understanding the factors that influence the success of transformation ("critical success factors") or advanced technologies ("cyber physical system", "emerging technologies")

The dispersion of research themes identified through keyword analysis underscores a high degree of knowledge fragmentation, which complicates the formulation of cohesive and practical insights from a managerial perspective.

The next section therefore synthesizes and systematically organizes the literature from a managerial perspective into four thematic categories: Impacts of transformation, Influencing factors, Barriers and challenges, Maturity models and readiness assessments.

Smart factory transformation from managerial perspective

The impacts of transformation

Smart production models, particularly smart factories, are expected to generate substantial positive impacts. A large body of research has investigated the outcomes of this advanced production paradigm from multiple perspectives. These studies provide a clearer picture of what successful transformation management can achieve. From the perspective of DC theory, evaluating these diverse impacts represents the 'sensing' phase, where firms scan the environment to identify the strategic potential and value created by digital adoption.

Many scholars emphasize the positive effects of transitioning to smart factories on production performance. For example, Zhu *et al*., (2024) drawing on the resource-based view and using a Difference-In-Differences (DID) approach with 16,441 firm-year observations from 2010 to 2020, demonstrate that smart manufacturing adoption significantly enhances labor productivity among publicly listed manufacturing firms in China. They further show that this relationship depends on internal resources (human capital quality and R and D intensity) as well as external conditions (industry competition). Similarly, Arcidiacono and Schupp (2024); Jung *et al*. (2023); Lyu *et al*. (2023); Opazo-Basáez *et al*. (2023); Shahzad *et al*. (2024) report that adopting smart manufacturing positively influences firms' operational performance, including cost efficiency, quality performance, delivery performance, improved resource allocation, and enhanced information-processing capabilities for decision-making. Shahzad *et al*. (2024) analyzing financial data from U.S. manufacturing firms between 2011 and 2021, find that smart manufacturing adoption reduces cost stickiness, thereby increasing cost flexibility, improving long-term performance, and enhancing firm value. Lyu *et al*. (2023) evaluating China's smart manufacturing pilot policies through a combined PSM and DID approach, confirm that smart manufacturing improves financial profitability. In contrast, Arcidiacono and Schupp (2024) argue that such transformation may have negative effects on financial performance. These contradictory findings may be attributed to the differing temporal scopes of the studies. While smart factory transformation is expected to yield superior financial efficiency in the long term, the initial stages of implementation often involve substantial capital expenditures and heightened operational complexity, which can temporarily suppress financial performance. Sensing these productivity and financial gains allows managers to perceive the competitive necessity of transformation, identifying it as a critical opportunity for future growth. Shukla and Shankar (2024); Xi *et al*. (2024) highlight that smart manufacturing strengthens organizational resilience in the face of disruptions such as the COVID-19 pandemic. Furthermore, Shukla and Shankar (2024) suggest that smart manufacturing adoption fosters innovation. In this context, sensing the resilience and innovation outcomes helps organizations recognize smart technologies as vital tools for navigating and adapting to turbulent market conditions.

Several studies also assess the impacts of smart manufacturing through a sustainability lens. These include improvements in environmental efficiency via increased investment in environmental protection, human capital expansion, and green technological innovation (Jin and Chen, 2024; Lyu *et al*., 2023; Wei *et al*., 2024), reductions in carbon emissions (Geng *et al*., 2024), and gains in green performance (Sun and Saat, 2023; Yang and Shen, 2023).

From a supply chain perspective, Kandarkar and Ravi (2024); Shukla and Shankar (2024) note that the adoption of smart technologies significantly enhances supply chain productivity, improves quality control, reduces defects, and strengthens product reliability across the chain. Additional benefits include improved labor utilization, shorter lead times, increased automation, reduction of repetitive tasks, process optimization, and stronger guarantees for information and data security. Smart manufacturing adoption also contributes to the development of industrial ecosystems. The ability to sense these interconnected benefits allows firms to perceive the potential for broader ecosystem-level advantages beyond their internal production lines.

The results of these studies present an overall picture of the outcomes achieved following a successful transformation into a smart factory or smart manufacturing system. Many research designs rely on static before-after comparisons or cross-sectional data, which fail to account for the lagged effects of technology adoption or the long-term sustainability of the reported gains. the current body of knowledge is characterized by an optimism bias, as most studies focus on successful implementations while overlooking failed transformations or the challenges of stalled digitalization efforts. It is evident that the reported benefits such as increased labor productivity, improved operational pe≤, ormance, enhanced financial outcomes, greener performance, and greater supply chain efficiency are essentially comparisons with the pre-transformation stage, prior to adopting a more advanced and intelligent model. However, existing studies have not addressed the relative priority of these impacts, namely which aspects firms are most eager to improve. This represents a potential research gap that deserves greater attention in future investigations.

Transformation influencing factors

Identifying the influence factors is critical for enabling successful transformation (Ghobakhloo and Ching, 2019; Sjödin et al., 2018). To advance the theoretical understanding of smart factory transformation, this section synthesizes influencing factors and barriers through the TOE framework (Baker, 2012; Tornatzky and Fleischer, 1990). The framework argues that technology adoption is contingent upon more than just technical features; it is shaped by the interplay between organizational capabilities and the external environment.

Technological factors

In the technological context, while there is a vast body of literature dedicated to the technical development of Industry 4.0, research that explicitly links these technological breakthroughs to managerial drivers remains relatively scarce. This scarcity underscores a persistent gap between technical engineering and strategic management. Among the reviewed articles, Li *et al*. (2024) provide a significant contribution by adopting the TOE-I framework, identifying digital infrastructure and technological breakthroughs not merely as tools, but as core strategic drivers that influence the overall advancement of smart manufacturing systems.

Organizational factors

Singh *et al*. (2024) examined the smart manufacturing transformation of manufacturing firms in Northern India and found that the key operational factors shaping the transition include internal R and D capability (investment in research and technological innovation). However, this study did not consider environmental and social dimensions. Jung *et al*. (2023) investigated the determinants of SMEs' intention to adopt smart factories in Korea. Their results demonstrated that the performance of the existing production system, perceived usefulness, and outsourcing experience had a clear impact on adoption intention. Arcidiacono and Schupp (2024); Chiang *et al*. (2024); Jang *et al*.(2023); C. Li *et al*. (2024); Neuhüttler *et al*. (2023) offered diverse perspectives in identifying internal factors that affect smart factory transformation. From a supply chain and leadership perspective, top management support, human resources and skills, internal collaboration and supply chain linkages, financial resources, and firm size emerged as critical factors in the study by Chiang *et al*. (2024); Li *et al*. (2024) revealed that organizational resilience, organizational culture, and entrepreneurial orientation are the core drivers influencing the advancement of smart manufacturing in manufacturing firms.

Environmental factors

Shukla and Shankar (2024); Stornelli *et al*. (2024), Singh *et al*. (2024) emphasized that government initiatives, supplier capabilities such as technology scouting and innovation learning, project execution capability (including project management, stakeholder coordination, resource and time management, testing and adjustment), knowledge transfer capability (training, documentation, technical support, and system fine-tuning assistance), supply chain capability (the ability to connect, coordinate, and integrate digital technologies), and market adaptability play a crucial role in supporting firms in adopting smart manufacturing. Park and Choi (2024) explored the role of regional context in smart factory adoption in Korea. Their findings revealed that regions with high industrial concentration exhibited stronger potential for implementing smart factories. Moreover, the structure of the regional workforce (e.g., the proportion of skilled and knowledge workers) and neighborhood effects significantly influenced regional-level smart factory adoption.

These operational, external, and internal organizational factors do not operate in isolation but rather require integration and balance (Jang *et al*., 2023; Ying *et al*., 2024). When combined, these factors form specific configurations of conditions that create distinct adoption pathways tailored to different types of firms (Li *et al*., 2024; Li and Zhao, 2024) such as the government and human resource-driven type, the environmental-organizational linkage type, and the organizational resilience-dominant type. In the study by Qu *et al*. (2023) multi-stakeholder sustainable requirements were categorized into prioritized levels: must-have (essential), attractive (value-enhancing), and indifferent (low-impact), to support firms during the design and business process reengineering phases of smart manufacturing system implementation. Similarly, Kim *et al*. (2023) through a meta-analysis of empirical studies on smart factories and smart manufacturing, primarily in the Korean context, identified and ranked the key factors influencing transformation as follows: (1) network effect, which exerts a dominant impact on adoption decisions; (2) social influence; (3) finance; (4) performance expectancy; (5) facilitating conditions; (6) technological capabilities and (7) entrepreneurship.

Barriers and challenges

Analyzing barriers and challenges helps managers anticipate and mitigate risks, including cost pressures, interoperability issues, skills shortages, and cybersecurity threats (Shi *et al*., 2020; Wang *et al*., 2022). It is evident that financial constraints, the absence of specialized suppliers, concerns about data security, insufficient understanding of the external environment and context, lack of commitment from top management, difficulties in managing data interfaces, limited government support, workforce training challenges, lack of environmental knowledge, organizational resistance to change, and technological limitations constitute major obstacles to firms' transition toward smart manufacturing (Agarwal *et al*., 2024; Atieh *et al*., 2023; Park *et al*., 2024). When considering transformation aligned with sustainable development, Liu *et al*. (2024) identify three overarching categories of barriers: Social (job transition pressures, social acceptance and adaptation, ethical concerns, regulatory frameworks, data security, and privacy); Economic (pressures of knowledge and technology absorption, financial costs and funding, supply chain management and collaboration, as well as uncertainties in the business environment and competitive dynamics); and Environmental (pollution, resource pressures, carbon emissions, and energy consumption). Furthermore, both Agarwal *et al*. (2024); Liu *et al*. (2024) provide rankings of the relative significance of these barriers.

By synthesizing the findings from the sources through the TOE framework, technological barriers are primarily characterized by cybersecurity threats, concerns over data security, and significant technical difficulties in managing data interfaces and ensuring interoperability between systems. Technological limitations and a lack of standardized protocols also hinder seamless integration. The organization transformation is heavily impeded by internal constraints, most notably high investment costs and financial pressures. Furthermore, a lack of commitment from top management, workforce skill shortages, and organizational resistance to change represent critical human and strategic hurdles that can stall progress. Externally, firms often struggle with limited government support and the absence of specialized suppliers capable of providing the necessary expertise and innovation support. Market uncertainties and complexities in the broader regulatory and competitive landscape further complicate the transformation journey.

While identifying impacts in Section 4.5.1 corresponds to sensing strategic opportunities, the seizing capability is defined by a firm's capacity to mobilize resources and proactively address constraints to capture those identified opportunities. By aligning the technological, organizational, and environmental drivers while simultaneously mitigating critical barriers organizations demonstrate the tactical synchronization required for actual implementation. This phase is vital for bridging the gap between recognizing theoretical potential and the practical execution of smart factory initiatives, ensuring that the necessary internal and external resources are effectively coordinated to achieve a successful transition.

Maturity models and readiness assessments

The use of readiness criteria and maturity models provides structured frameworks to assess current capabilities, benchmark progress, and design sequenced roadmaps for implementation (Mittal *et al*., 2020; Schumacher *et al*., 2016). Recent studies demonstrate a variety of approaches while also revealing several limitations. From DC theory lens, the transforming capability is essential for the systematic and continuous reconfiguration of organizational assets to achieve sustained digital maturity. By utilizing multidimensional frameworks to define a 'desired maturity' level, firms can move beyond static technological adoption toward a goal-oriented and prioritized transformation roadmap. This process of continuous alignment ensures that the organization can effectively reconfigure its strategic, technological, and human dimensions to maintain long-term competitiveness and adaptability within a rapidly evolving industrial landscape.

For instance, (Shukla and Shankar, 2024b) propose a generalized model for Indian SMEs, comprising six criteria (smart technology infrastructure, economic, people and awareness, organization and culture, process capability, and supply chain management) and five readiness stages (from precontemplation to maintenance). This framework proves useful in analyzing actual readiness levels and suggesting solutions for improvement.

Similarly, Sajadieh and Noh (2024) extend the readiness model to the context of the Urban Smart Factory, integrating dimensions such as sustainability, resilience, and people (skills, health, social impact). This highlights that readiness goes beyond technology and organization, requiring consideration of environmental and social contexts.

Other contributions have focused on self-assessment tools or detailed roadmaps. Modrak et al. (2024) provide a useful self-assessment model for SMEs. Ejaz (2023) adjusts an existing model to measure the gap between current and desired states, suggesting the adoption of multidimensional frameworks (technical-managerial-human) for more effective implementation. Zhao *et al*. (2023) develop the PIMRI model with six stages, enabling firms to identify their position, prioritize investments, and benchmark against peers. Cha *et al*. (2023) shift attention to supplier capability maturity, while Wang et al. (2022) emphasize four core domains (production, technology and equipment, management, innovation and development) to guide step-by-step roadmaps.

At the methodological level, Çınar *et al*. (2021) integrate maturity assessment with technology forecasting to predict developmental trajectories, while Shi *et al*. (2021) employ hybrid AI-metaheuristics to identify capability gaps and support targeted improvement pathways. Other works have developed models for specific SME contexts, such as Rahamaddulla *et al*. (2021) in Malaysia with a 4M-based framework, or Lin *et al*. (2020), who apply SIRI to Taiwanese enterprises and confirm the interdependence among Process, Technology, and Organization.

A critical evaluation of existing maturity models reveals a significant methodological and conceptual gap. Most frameworks remain technologically biased, frequently underemphasizing the roles of governance, leadership, and cybersecurity readiness. Furthermore, current models are largely static and descriptive, serving as snapshots of current capabilities rather than dynamic, goal-oriented tools that incorporate forecasting and prioritization. The lack of empirical validation using primary data also raises concerns regarding the practical generalizability of these models across different industrial scales and regional contexts.

Overall, existing studies offer diverse approaches to assessing readiness and maturity, ranging from general frameworks to context-specific models by industry, scale, or geography. Nevertheless, a critical gap remains: the absence of a comprehensive model that not only evaluates current status but also establishes future objectives, provides an optimized and prioritized roadmap, and incorporates forecasting to prepare firms for rapidly evolving technological and market environments. Therefore, further research is needed to develop an integrated model combining assessment, goal-setting, action planning, and predictive mechanisms to better support firms in their transformation toward smart factories.

Managerial implications

Managing smart factory transformation necessitates a strategic shift from viewing it as a mere technological upgrade to a systemic organizational reconfiguration. To move beyond generic insights, practitioners should adopt a structured approach based on these specific guidelines:

Diagnostic baselines and goal-setting

Rather than simply adopting technology, firms should first utilize multidimensional maturity models to benchmark their current status across technology, management, and human domains. Crucially, managers must define their "desired maturity" level, which ensures that every investment is mapped to a specific future state rather than just reacting to current inefficiencies.

Prioritized roadmapping

Successful implementation requires a sequenced roadmap where firms differentiate between "must-have" (essential) and "attractive" (value-enhancing) requirements. Practitioners are advised to prioritize internal resource capabilities such as top management support, R&D intensity, as these are the foundational drivers that determine the success of technological adoption.

Context-specific adoption pathways

Firms should identify their specific adoption type to tailor their resource allocation according to regional industrial concentrations and workforce structures.

Proactive risk and barrier mitigation

Managers must anticipate the complex trade-off between high short-term capital expenditures and long-term financial efficiency. Actionable governance must prioritize the removal of primary bottlenecks, specifically cybersecurity readiness, data interoperability, and workforce skill shortages, which often pose the greatest threat to scaling smart manufacturing initiatives.

By integrating these prioritized actions, firms can transition from fragmented digitalization efforts toward a holistic and goal-oriented transformation governance model.

FUTURE RESEARCH DIRECTION

The descriptive bibliometric analysis reveals that research themes related to the transformation toward smart factories cover a wide range of organizational, human, social, and environmental dimensions. This diversity has led to fragmented knowledge, making it difficult to identify an effective transformation roadmap. Content analysis provides a clearer overall picture of how this transition has been studied. From a managerial perspective, however, the focus extends beyond merely identifying factors, barriers, or maturity models. What matters most is understanding how these elements interact and leveraging their interconnections to ensure that transformation is not just a one-time achievement but a continuous, organization-specific process that supports long-term development and sustained effectiveness.

Studies on impacts have reported notable outcomes such as higher labor productivity, improved operational performance, better financial results, greener outcomes, and enhanced supply chain efficiency (Lyu *et al*., 2023; Shahzad *et al*., 2024). However, these findings are primarily framed as before-after comparisons, without clarifying the prioritization of outcomes that firms seek to improve. This represents an important gap, since prioritization of impacts directly shapes how firms allocate resources and design their transformation roadmap.

Similarly, research on influencing factors has highlighted the critical roles of human capability, organizational culture, change management, and technological infrastructure (Chiang *et al*., 2024; Li *et al*., 2024). Yet, little is known about the relative priority among these factors in practice. For instance, some firms may need to strengthen their technological infrastructure first, while others may need to prioritize workforce training and cultural change to ensure that technologies are effectively adopted.

Research on barriers has also identified challenges such as high investment costs, skill shortages, resistance to change, and complexity in technology integration (Shi *et al*., 2020; Wang *et al*., 2022). Still, there is a lack of evidence on which barriers should be addressed first in order to avoid delays and inefficient resource allocation in the early phases of transformation.

Finally, research on readiness and maturity models has provided useful frameworks and staged roadmaps that allow firms to assess their current position and identify future targets. A promising approach is to integrate the concept of "desired maturity" (Modrak *et al*., 2024), whereby firms not only assess their current state but also define their target maturity level, from which a prioritized roadmap can be designed. For example, if a firm already has strong production capabilities, prioritizing investment in smart production could deliver faster and more tangible value.

Taken together, these findings highlight the lack of a comprehensive, integrated model that not only prioritizes the organization's direction, assesses readiness levels but also defines "desired maturity," sets future goals, establishes prioritized roadmaps, and incorporates forecasting to ensure long-term adaptability. Future research should therefore focus on developing the transformation management models for smart factories that are:

- Multidimensional: addressing technology, organization, human resources, supply chain, and sustainability.
- Goal-oriented: identifying target states rather than only reflecting the current situation.
- Prioritized: enabling firms to allocate resources efficiently through staged implementation.

Such an integrated model represents a necessary research direction that could significantly advance both theory and practice in managing the transformation toward smart factories.

CONCLUSION

Smart factory transformation has emerged as a crucial pathway for firms to remain competitive in the era of Industry 4.0. While existing studies demonstrate clear benefits ranging, the fragmented knowledge creates difficulties in defining effective and prioritized transformation roadmaps. To address this gap, our study provides a comprehensive review that synthesizes findings across these four dimensions and highlights the missing focus on prioritization. By integrating ideas such as desired maturity, stepwise roadmaps, and forecasting, future research can move toward developing governance models that not only assess readiness but also guide firms in setting goals, allocating resources, and sequencing actions effectively. Overall, the findings offer both scholars and practitioners a clearer foundation for designing tailored and sustainable transformation pathways toward smart factories.

Despite its contributions, this study is subject to several limitations that should be acknowledged. First, the review relies exclusively on articles indexed in the Scopus database and published in English between 2015 and 2024. While Scopus provides a vast range of academic publications, this singular focus may result in a partial representation of the global research landscape. To enhance the breadth and validity of future research, it is highly recommended to incorporate multiple databases, such as Web of Science, IEEE Xplore, or Google Scholar. This language and database restriction may have excluded relevant studies available in other databases or written in non-English languages, potentially leading to a partial representation of the global research landscape. Second, while the combination of bibliometric and content analysis enhances objectivity and depth, the interpretation of qualitative findings still involves a degree of subjectivity inherent in manual coding and thematic classification. Finally, the research relies on secondary data from published studies and does not include empirical validation. Future work should build on these findings by integrating primary data collection and employing quantitative or mixed-method approaches to empirically test the conceptual relationships and proposed frameworks identified in this review. Acknowledging these limitations offers valuable guidance for subsequent research seeking to expand and validate the knowledge base on smart factory transformation from both theoretical and practical standpoints.

ABBREVIATIONS

AI: Artificial Intelligence; **CPS:** Cyber-Physical Systems; **DID:** Difference-In-Differences; **DC:** Dynamic Capabilities; **IF:** Impact Factor; **IIoT:** Industrial Internet of Things; **IoT:** Internet of Things; **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses; **PSM:** Propensity Score Matching; **R and D:** Research and Development; **SCI:** Science Citation Index; **SIRI:** Smart Industry Readiness Index; SJR: SCImago Journal Rank; **SMEs:** Small and Medium-sized Enterprises; **TOE:** Technology-Organization-Environment; **TOE-I:** Technology-Organization-Environment-Innovation; VOSviewer: Visualization of Similarities Viewer; **IT-OT:** Information Technology–Operational Technology; **ML:** Machine Learning.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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