Industrial Digitalization &Digital innovation: Systematic Literature Review and Bibliometric Analysis

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Abstract:
In recent years, manufacturing industries have accelerated digital transformation by adopting technologies associated with the Industry 4.0 paradigm [1]. The Fourth Industrial Revolution integrates cyber–physical systems (CPS), pervasive connectivity, and embedded intelligence across design, shop-floor operations, and in-service use, enabling fully networked smart manufacturing systems [2]. Since 2020, COVID-19 disruptions and intensifying competition have further emphasized the need for remote operations and organizational resilience [3], prompting firms to deploy digital tools not only for productivity and efficiency but also for agility and sustainability. Many countries have launched strategic initiatives, such as Germany's Industrie 4.0 and China's Made in China 2025, to leverage digital technologies for innovation and improved industrial performance [4,5].
At their core is a set of interconnected information technology (IT) capabilities [6]: industrial automation and robotics [7], the Industrial Internet of Things (IIoT) [8], cloud computing [9], artificial intelligence (AI) [10], and big data analytics [11]. In practice, automated equipment and robots instrumented with IIoT sensors stream real-time data to cloud platforms, where AI and big data models detect anomalies, predict failures, and optimize operations; insights are then fed back for adaptive control, closing the CPS loop. While Industry 4.0 emphasizes autonomy, interoperability, and real-time optimization, the emerging Industry 5.0 paradigm [12] extends the vision by centering human value creation and resilience through advanced human–machine collaboration. Despite clear benefits, adoption introduces challenges and risks [13], including heightened cyber security and safety concerns [14] and tensions with sustainability targets [15]. Other key obstacles include legacy system integration, solution selection amid rapid tool proliferation, limited interoperability standards, fast technology cycles that threaten longterm compatibility, data quality and bias issues in AI, and workforce upskilling needs [16]. Consequently, it is essential to understand not only the individual capabilities of these technologies but also their convergence, integration pathways, and barriers to realizing their full potential. To support a better understanding of the evolving digital landscape and its challenges, this review sets out two main objectives: • Synthesize recent research on smart manufacturing ecosystems—state of the art, key challenges, and future directions for Industry 4.0 and Industry 5.0, with emphasis on flexibility, adaptability, and scalability. • Propose and validate a framework that reengineers core business processes across functional areas in industrial companies. The main contributions of this paper include:

Keywords: digitalization; digital transformation; industrial companies; manufacturing automation; industrial robotics; internet of things (IoT); industrial internet of things (IIoT); cloud computing; artificial intelligence (AI); big data analytics

INTRODUCTION

1. A systematic literature review of manufacturing digitalization technologies and tools from the perspectives of evolutionary development and

application needs; 2. An integrated mechanism for implementation and for assessing capabilities and improvement potential across manufacturing processes; 3.Actionable guidance for planning and evaluating investments in Industry 4.0 and related digital technologies, including applicability to SMEs. The remainder of this paper is organized as follows: Section 2 details the research methodology, including database selection and analytical methods for processing. Section 3 synthesizes prior reviews on innovative digitalization technologies identifying unresolved questions. Section 4 presents a thematic review of research articles drawn from our corpus, highlighting publication trends and the evolution of core themes. Section 5 introduces a systematic framework for industrial digitalization and demonstrates its applicability and effectiveness through a proof-of-concept deployment and a SIRI-based maturity assessment. Section 6 analyzes key challenges and emerging opportunities for manufacturing digitalization, with attention to flexibility, adaptability, and scalability in the contexts of Industry 4.0 and Industry 5.0. The last section concludes by summarizing the main findings, outlining implications for theory and practice, offering guidance for stakeholders, and proposing directions for future research.

2. Research Methodology The methodological process was designed to capture recent and impactful research on digital transformation in industrial companies, with emphasis on key technological enablers. The study followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [17], a widely recognized protocol for structured literature reviews in technical domains (Supplementary Materials). To capture the core technologies underpinning contemporary smart manufacturing, we focused on English-language, peer-reviewed journal articles and review papers published from 2020 through to the search date. This window prioritized the field's rapid evolution and the most recent contributions. Consistent with our open-science stance, we applied an Information 2025, 16, 1080 3 of 26 open-access filter to ensure full-text availability for analysis. Searches were conducted in two major bibliographic databases—Scopus and Web of Science (WoS) (Figure 1).

A. Figures and Tables

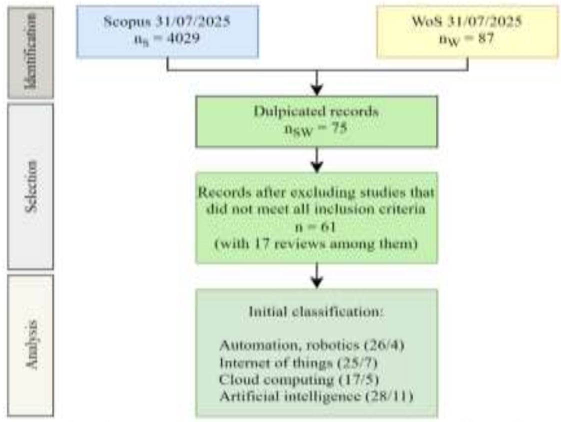

Figure 1. Overall literature review process following PRISMA guidelines. Remarks:

2. 3. Literature survey

All identified documents were screened and assessed for eligibility, after which they were initially classified by digital technologies [6]. The numbers in parentheses indicate the total number of articles, followed by the number of review articles shown as total/reviews for each main classification group. The database queries returned 4029 records from Scopus and 87 from WoS. To ensure quality and relevance, we retained only articles indexed in both Scopus and WoS, yielding 75 publications. Manual screening then excluded seven records that did not meet full open-science criteria (e.g., institution-restricted access) and seven records whose focus was predominantly economic, managerial, or educational, with insufficient technological analysis. The final dataset comprised 61 articles: 17 review papers providing consolidated insights and thematic syntheses, and 44 original research articles presenting technological developments or empirical findings. We included peer-reviewed journal articles (Research Article or Review Article) published in English between 2020 and 2025, with open-access full text available, indexed in both Scopus and WoS, situated in industrial or manufacturing contexts. We excluded duplicates; items without open-access; non-journal formats (editorials, letters, notes, conference abstracts); studies outside industrial or manufacturing domains; papers focused solely on economic, organizational, or educational themes without material technological analysis; and records indexed in only one of the two databases. Beyond PRISMA, the analysis proceeded in three complementary steps that combined bibliometric meta-analysis with qualitative review. First, we computed yearly publication frequencies, fitted linear trend lines for publication counts and author keywords, and conducted a keyword co-occurrence analysis. Second, two researchers independently coded full texts and abstracts, grouped codes into themes, and reconciled discrepancies through discussion to reach consensus on the final topic set without relying on automated topic modeling software. Third, we synthesized these results to propose a systematic Information 2025, 16, 1080 4 of 26 framework for industrial digitalization, selecting the most appropriate technologies for key functional activities and work processes. To establish validity, we implemented proof of concept (PoC) and assessed digitalization maturity using a multi-criteria approach. The methodology both maps the digital transformation landscape and supports the development and empirical validation of the proposed framework, thereby ensuring transparency and reproducibility. 3. Related Work: Review Articles on Industrial Transformation This section reviews prior review articles from the selected corpus to establish the study's foundation. Collectively, these works provide a consolidated perspective on industrial digitalization and outline practical applications. Several reviews are technology-centered, with AI and machine learning (ML) dominating the focus. Çınar et al. [18] review ML for predictive maintenance, identifying supervised methods such as random forests, support vector machines, and neural networks as prevalent, while noting low industrial adoption and advocating hybrid models and cloud-based solutions. Burzy ´nska [19] examines AI/ML in defect diagnosis within a Quality 4.0 context, highlighting strong model accuracy but significant data-quality and deployment barriers. Gargalo et al. [20] analyze hybrid modeling in (bio)chemical engineering, showing its potential for optimization and sustainability alongside integration and interpretability challenges. Ghosh et al. [21] evaluate AI-driven surface-roughness assessment, noting deep-learning effectiveness but a lack of benchmark datasets and transparency. A distinct cluster of reviews addresses digital-twin (DT) technology and its integration. Onaji et al. [22] present a layered DT framework for manufacturing, emphasizing predictive-maintenance and optimization benefits while noting infrastructure challenges, and Wang et al. [23] highlight DT's role in improving efficiency and sustainability in the energy sector. Other reviews focus on integrating digitalization with established operational philosophies. Escobar et al. [24] discuss the transition to Quality 4.0 and recommend AI-enhanced predictive analytics supported by mechanisms for explainability. Benslimane et al. [25] examine the convergence of Lean Manufacturing and Industry 4.0, identifying mutual benefits as well as cultural, technical, and skills-related barriers. Suuronen et al. [26] adopt strategic and ecosystem perspectives by examining Digital Business Ecosystems (DBEs) and their enabling conditions, benefits, and obstacles. Serey et al. [27] propose a framework that aligns Industry 4.0 adoption with organizational strategy. Voinea et al. [28] map industrial augmented-reality (AR) trends, noting integration with AI and IoT but highlighting cost and usability issues. Salierno et al. [29] compare Europe's "digital factory" with China's "cloud manufacturing" and identify interoperability as a shared challenge. Sector- and connectivity-specific studies include those of Isoko et al. [30], who investigate Industry 4.0 enablers in biopharmaceutical manufacturing and call for standardized integration models, and Qiu et al. [31], who review IIoT adoption and advocate fully integrated architectures combining 5G, cloud, edge

AI, and DT. Kamble et al. [32] propose a performance-measurement framework for automotive small and medium-sized enterprises (SMEs). Reyes Domínguez et al. [33] provide bibliometric and cross-technology perspectives by exploring global Industry 4.0 research trends and urging stronger integration of sustainability with emerging technologies, while Wang and Jiao [34] focus on human–automation collaboration using adaptive AI and cognitive modeling. Several of the 17 reviewed studies outline strategic or conceptual frameworks to guide smart manufacturing under the Industry 4.0 paradigm, each addressing different aspects such as technology integration, performance measurement, strategic alignment, or operational intelligence:

The purpose of this section is to present shortly what DI is, what we know and don't know about it. We define DI, state its characteristics, types, the benefits, and risk associated with it, as well as success conditions that matter for DI processes, outputs, and outcomes. In line with the latest scientific guidelines for conducting bibliometric research, bibliometric analysis as in our case, is considered already a literature review tool, thus we build on (Öztürk et al. 2024, who suggested the following structure): (1) Defining the aim of the research; (2) Collecting data on the relevant literature; (3) Analysis and visualization; (4) Interpreting the findings and results. Following these guidelines, our theoretical background section is focused on DI, for the purpose of presenting the key contributions on this concept.

B. Figures and Tables

Table 1. Topic evolution in industrial digitalization (2020–2025).

Period	Concise Focus	Key Threads	Sources
2020–2021	Foundations, then consolidation with quality and sustainability	IoT/IIoT, CPS, edge-cloud, blockchain, security, performance measurement/optimization, PdM; by 2021: Quality 4.0, Green IoT/I5.0	[18,24,32,36,38,39]
2022	Human-centered turn and ecosystems/servitization; deeper data/operations layers	Industry 5.0, digital ecosystems/servitization, IoT + big-data pipelines, SCADA/ICS modernization	[22,40,42,43]
2023	AI/ML scale-up on the shop floor and governance	Defect detection, process optimization, digital-transformation governance, skills/HMI (human-centric I5.0)	[45,48,49,52]
2024	Application pivot and maturity	Real-time machine-vision QC, DT/robotic simulation (Unity/ROS), maturity models, bioprocessing 4.0, sensor-fusion (digital shadows, AE)	[25,53,55,63]
2025 *	Synthesis and pragmatism	Reference architectures/reviews (IIoT, AI-enhanced DT/industrial metaverse), low-cost SME methods (current-sensor "fingerprints"), sectoral digitalization and sustainability (e.g., furniture)	[31,64]

Notes: The list of abbreviations used in the table is provided in [33]. The asterisk (*) indicates that the data for 2025 refer only to the first half of the year.

Our definition of DI is based on the recent grounded theory review research conducted by Hund et al. (2021), describing *"the creation or adoption, and exploitation of an inherently unbounded, value-adding novelty (e.g., product, service, process, or business model) through the incorporation of digital technology"* (p. 6). This definition integrates three perspectives offered earlier by Nambisan et al. (2017), such as the output perspective in form of new products, services, platforms, created value and experiences; the integration perspective of digital technologies and infrastructure perspective (e.g., digital platforms, AI, blockchain, 3D printing, quantum computing) enabling DI processes; and finally contextual perspective, outlining the possibilities of innovation to be applicable across different contexts and contributing to real world change. For more enhanced understanding, we will refer in this paper to DI processes, outputs, and outcomes, which build upon those perspectives. This view aligns with latest research of Yoo et al. (2024), who suggest that it is important to use the conceptualization of DI as it *"implicates using various digital resources to create value, differentiating it simultaneously from physical and IT."* (p.4). Compared to IT, that has been mostly focused on technological capabilities, the term digital has more emphasis on value creation in innovation processes. Researchers also argue that with the widespread of emerging technologies, such as AI tools, there is a big shift in conceptualizing technology beyond the traditional IT function (see e.g., Malhotra and Majchrzak 2024), that is why we focus on DI and outline its characteristics next.

Conclusion

This study reviews the state of industrial digitalization (2020–July 2025), synthesizing developments across classical Industry 4.0 technologies, operations and process improvement, Quality 4.0, and simulation/modeling (AI/ML and digital twins), while tracing the rise of Industry 5.0's human-centric and sustainability priorities. We organize the literature longitudinally, quantify topic salience by year, and highlight how the field shifts from technology deployment to integrated, impact-oriented practice. Building on this synthesis, we propose a layered, company-level framework that embeds intelligence across physical, edge, fog, cloud, and decision-support layers to enable low-latency control, coordinated operations, and strategic alignment. A field-based validation links framework-guided interventions to improvements in SIRI maturity and operational outcomes, indicating that even partial deployment can enhance flexibility, reduce lead times, and strengthen financial performance. For practitioners, the framework offers a phased path (particularly suitable for SMEs) from low-cost sensorization and edge analytics toward fog/MES coordination and cloud/AI capabilities, complemented by decision-support mechanisms that preserve human oversight. For researchers and policymakers, the results motivate work on interoperable standards, explainable AI for maintenance/quality, and ecosystem-level evaluation. The proposed holistic framework has several advantages: • Reveals interdependencies among technologies, resources, and organizational capabilities across time and layers (shop floor, MES/ERP, enterprise level). • Enables dynamic orchestration of IT/OT by clarifying when and how to integrate automated systems, cloud computing, and AI so they reinforce one another rather than operate in isolation. • Prevents fragmented initiatives in which isolated projects and siloed technology stacks create inefficiencies and duplicate costs. • Supports SMEs through modular, phased adoption (low-cost sensorization–edge analytics–fog/MES coordination–cloud/AI), use of open standards to avoid vendor lock-in, and the option to leverage managed cloud services to reduce upfront investment and IT burden. By embedding intelligence across the physical, edge, fog, cloud, and decision-support layers, the framework supports low-latency control, coordinated operations, and resilience.

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