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The Role of Industrial Operators and IIoT in AI/ML-Based Process Optimization: A Bibliometric Analysis and Research Gap Identification in the Industry 4.0 Era

Renda Sandi Saputra[1*], Rifki Saefullah[2]

[1] *Master of sains program, Faculty of Informatics and Computing, university Sultan Zainal Abidin, Kampung Gong Badak, 21300, Terengganu*

[2] *Communication in Research and Publications, Bandung, Indonesia*

**Corresponding author email: rendasandi8888@gmail.com*

Abstract

The rapid adoption of Artificial Intelligence (AI) and Machine Learning (ML) technologies has transformed manufacturing systems under the Industry 4.0 paradigm, enabling data-driven process optimization, predictive decision-making, and intelligent production management. Despite substantial growth in this research domain, previous bibliometric studies reported limited visibility of the Industrial Internet of Things (IIoT) and industrial operators within the AI/ML-based process optimization literature. This study aims to examine the evolution of these research themes and assess how the knowledge structure of the field has developed during the transition from Industry 4.0 to Industry 5.0. A bibliometric analysis was conducted using 362 publications retrieved from Dimensions.ai covering the period 2020–2026. Bibliometric performance indicators were analyzed using Bibliometrix (R), while science mapping and keyword co-occurrence analyses were performed using VOSviewer 1.6.20. The results reveal a continuous increase in publication output and the emergence of six major thematic clusters. AI and Smart Factory technologies remain the dominant research themes, followed by Smart Manufacturing and Cyber-Physical Systems. The analysis further shows that IIoT has evolved into a distinguishable thematic component connected to industrial connectivity, edge computing, and sensor infrastructures. In addition, a new human-centered cluster has emerged, characterized by concepts such as Operator 4.0, human-in-the-loop systems, collaborative robotics, and human-centered AI. Although both IIoT and operator-related themes have gained visibility, their thematic prominence remains lower than that of the dominant AI and smart manufacturing clusters. The findings indicate a gradual shift toward a more integrated manufacturing paradigm that combines intelligent algorithms, industrial connectivity, and human expertise, reflecting the broader transition from Industry 4.0 to Industry 5.0.

Keywords: Smart manufacturing, process optimization, industrial internet of things, human-centered manufacturing, bibliometric analysis

1. Introduction

The rapid evolution of Industry 4.0 has transformed manufacturing systems from conventional production environments into highly interconnected, data-driven ecosystems. This transformation is enabled by the integration of Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), cloud computing, big data analytics, and Artificial Intelligence (AI), allowing production processes to operate with unprecedented levels of automation, adaptability, and real-time decision-making. As a result, manufacturing organizations increasingly rely on digital technologies to improve productivity, quality assurance, resource efficiency, and operational sustainability (Frank et al., 2019; Barua et al., 2025).

Among the enabling technologies of Industry 4.0, Artificial Intelligence and Machine Learning (AI/ML) have emerged as key drivers of industrial process optimization. AI/ML techniques are now widely applied to predictive maintenance, quality control, process monitoring, scheduling, anomaly detection, and energy management. These capabilities allow manufacturing systems to move beyond reactive decision-making toward predictive and prescriptive operations, generating measurable improvements in productivity, reliability, and operational performance (Ghahramani et al., 2020; Kang et al., 2020). Consequently, AI-driven optimization has become one of the most dynamic and rapidly expanding research domains within smart manufacturing.

The growing importance of AI/ML in manufacturing is reflected in the increasing volume of scholarly publications. Several review and bibliometric studies have documented substantial growth in Industry 4.0 and smart manufacturing research over the last decade (Muhuri et al., 2019; Adithya et al., 2025). More specifically, Mateo and Redchuk (2024) mapped the scientific landscape of AI and machine learning as drivers of process optimization within the Industry 4.0 framework. Their analysis identified dominant themes related to smart factories, digital integration, cyber-physical systems, and organizational strategy. However, despite the recognized importance of industrial connectivity and human involvement in manufacturing systems, neither IIoT nor industrial operators emerged as prominent thematic constructs in the resulting knowledge structure.

This finding is particularly noteworthy because IIoT constitutes the primary infrastructure through which AI/ML systems obtain operational data. Industrial sensors, connected devices, edge computing platforms, and communication networks continuously generate large volumes of real-time information that enable predictive analytics and intelligent process control. Recent studies have demonstrated that the effectiveness of AI-based optimization is highly dependent on the quality, availability, and integration of IIoT-generated data streams (Frankó et al., 2022; Wang et al., 2024). Nevertheless, the extent to which IIoT has evolved into a distinct research theme within the broader AI/ML process optimization literature remains unclear.

At the same time, the role of the industrial operator has undergone substantial transformation. Early Industry 4.0 narratives frequently emphasized automation and autonomous decision-making, often portraying human involvement as progressively diminishing. More recent developments, however, suggest a different trajectory. The concepts of Operator 4.0, Human-Centered AI, and Human-in-the-Loop manufacturing emphasize collaboration between intelligent systems and human expertise rather than the replacement of human workers (Romero et al., 2016; Mentzas et al., 2024). Operators increasingly function as supervisors, decision-support users, knowledge contributors, and ethical overseers within AI-enabled production environments. This evolution has become even more prominent with the emergence of Industry 5.0, which places human-centricity, resilience, and sustainability at the center of industrial transformation (Breque et al., 2021).

Despite these technological and conceptual developments, the relationship among AI/ML, IIoT, and industrial operators remains fragmented within the existing literature. While individual studies have investigated AI applications, IIoT architectures, or human-centered manufacturing independently, relatively little is known about how these dimensions collectively shape the knowledge structure of process optimization research. Furthermore, it remains unclear whether the gaps identified by Mateo and Redchuk (2024) have narrowed as Industry 5.0 concepts gained prominence and as real-world deployments of AI-enabled manufacturing systems expanded.

Bibliometric analysis provides a suitable methodological approach for addressing this issue because it enables systematic mapping of scientific knowledge, identification of thematic structures, and detection of emerging research trends. By combining performance analysis with science mapping techniques, bibliometric methods can reveal how research themes evolve over time and how different concepts are interconnected within a scientific field (Donthu et al., 2021; Moral-Muñoz et al., 2020). Such an approach is particularly valuable for evaluating whether IIoT and industrial operators have become more visible within the AI/ML-driven process optimization literature and for identifying unresolved research gaps that require further investigation.

Therefore, this study conducts a bibliometric analysis of publications related to AI/ML-based process optimization in the context of Industry 4.0 and Industry 5.0. Using data retrieved from Dimensions.ai, with comparisons made to previous Scopus-based studies, this study examines the evolution of publication trends, thematic clusters, and research networks during the 2020–2026 period. Particular attention is given to the positioning of IIoT and industrial operators within the knowledge structure of the field. By extending and updating the findings of Mateo and Redchuk (2024), this study seeks to determine the extent to which the operator–IIoT–AI/ML triad has emerged in the literature, identify remaining research gaps, and propose future directions for human-centric and intelligent manufacturing research.

2. Literature Review

2.1. Industry 4.0: From Concept to Data-Driven Ecosystem

Industry 4.0 emerged as a strategic initiative from the German government in 2011 and has since evolved into a globally recognized manufacturing paradigm. Its defining characteristic is the fusion of physical production systems with digital information and communication technologies through CPS, enabling what Ibarra et al. (2018) describe as the transformation of factories into smart environments. Ruiz-Sarmiento et al. (2020) identify networked collaboration between processes and machines, for continuous data collection, exchange, and analysis as the foundational operational principle of the paradigm.

The scale of digital data generated by Industry 4.0 systems is unprecedented. Ghahramani et al. (2020) characterize smart manufacturing as a data-driven approach that leverages IoT devices and monitoring sensors to enable self-optimization, making the management and processing of industrial data one of the central engineering challenges of the decade. Barua et al. (2025), in a recent study of AI strategies and barriers in Industry 4.0, note that since 2020 AI for operations planning has matured from heuristic add-ons to learning-based controllers capable of dynamic scheduling, computer-vision quality assurance, and closed-loop optimization. The transition from Industry 4.0 to Industry 5.0 represents a qualitative shift in priorities: from efficiency and automation to human-centricity, resilience, and environmental sustainability. The European Commission's Industry 5.0 framework (Breque et al., 2021) explicitly repositions technology as a servant of human values rather than an end in itself, a framing that directly elevates the role of the operator in production systems and challenges the AI Factory model described by Iansiti and Lakhani (2020).

2.2. AI/ML as a Driver of Industrial Process Optimization

The application of AI/ML to industrial process optimization spans a wide range of techniques and use cases. Kang et al. (2020) provide a systematic literature review of ML applications in production lines, identifying predictive maintenance, quality control, and process parameter optimization as the three most prevalent application domains. Erozan (2019) demonstrates the value of fuzzy logic systems for maintenance decision support in complex manufacturing environments. Ghahramani et al. (2020) apply evolutionary computing and deep learning to semiconductor manufacturing, demonstrating improvements in yield and cycle time. More recent work has extended these applications. Frankó et al. (2022) apply ML to IIoT-generated data streams for quality control, proactive maintenance, fault detection, and safety assurance in smart production environments. Adithya et al. (2025), in a comprehensive bibliometric analysis of smart factory research covering 1,625 Scopus records from 2014 to 2024, document the thematic evolution from foundational Industry 4.0 technologies toward Industry 5.0 priorities, with sustainability and human-centricity as the two most prominent emerging themes. Samuels (2025) identify the integration of supply chain AI from Industry 4.0 to 6.0 as a growing frontier, particularly for decision-making support and operational resilience.

A consensus has emerged in the literature that the technical feasibility and measurable benefits of AI/ML in manufacturing are no longer in question (Mateo & Redchuk, 2024). The open frontier is the democratization of these capabilities, making AI/ML accessible and actionable for the operators and engineers who manage industrial processes, rather than limiting its value to data scientists and IT specialists (Barua et al., 2025).

2.3. IIoT: From Connectivity to Intelligence

The IIoT provides the sensor, connectivity, and edge computing infrastructure that enables AI/ML models to operate on real-time industrial data. Porter and Heppelmann (2015) established the foundational insight: combinations of sensor readings linked to operational states can predict failures and enable optimization at a level of granularity previously impossible with manual inspection or periodic sampling. Ruiz-Sarmiento et al. (2020) operationalize this insight in a predictive maintenance model that integrates IIoT sensor data with ML algorithms to anticipate machinery failures in an Industry 4.0 context.

The technical architecture of IIoT systems has matured substantially since the foundational work. Frankó et al. (2022) provide a detailed overview of the layered IIoT architecture, spanning sensor nodes, edge gateways, fog computing layers, and cloud platforms, and map ML algorithms to specific layers based on latency, data volume, and computational requirements. Wang et al. (2024) demonstrate real-world IIoT deployment for production monitoring and process automation in the automotive sector, using OPC UA protocols, digital twin integration, and deep Q-network reinforcement learning for automated process transitions. Redchuk et al. (2023) provide one of the few empirical case studies of IIoT and ML co-deployment for energy efficiency improvement in a process manufacturing firm, reporting measurable reductions in energy consumption and validating the integrated Operator–IIoT–AI/ML model in a real industrial setting. Despite this technical maturation, the bibliometric finding of Mateo and Redchuk (2021), that IIoT does not appear as a dominant keyword in the AI/ML–process optimization–Industry 4.0 literature suggests a persistent disconnect between the technical IIoT literature and the broader industrial AI literature. This study tests whether this disconnect has been bridged in the 2021–2026 period.

2.4. The Industrial Operator: From Displaced Worker to Intelligent Collaborator

The role of human operators in AI-enabled industrial environments has been a subject of significant debate and evolving conceptualization. The AI Factory model proposed by Iansiti and Lakhani (2020) foregrounds autonomous AI decision-making and positions humans at the edge of the critical value delivery path, a perspective that, while influential, has been critiqued for undervaluing human agency, tacit knowledge, and ethical oversight in industrial operations. The Operator 4.0 concept (Romero et al., 2016) offers an alternative framing, positioning the worker not as a passive recipient of AI outputs but as an intelligent collaborator who co-operates with AI systems through a range of interfaces: augmented reality overlays, exoskeletons, collaborative robots (cobots), and wearable monitoring systems. Cunha et al. (2022), in a systematic review of the operator's status in Industry 4.0 based on Scopus data, confirm that the operator role is undergoing a profound transformation but that the scientific literature has yet to develop a comprehensive framework for managing this transition in practice.

Mentzas et al. (2024) extend this critique to the AI research community directly, arguing that the evolution of AI capabilities in manufacturing has not been matched by equivalent progress in human-centered processes. They propose Human-Centered AI (HCAI). which embeds transparency, controllability, and human oversight as design requirements rather than afterthoughts, as a foundational principle for Industry 5.0. The concept of Human-in-the-

Loop (HITL) manufacturing, recently reviewed by Bajestani et al. (2026) in the context of large language models and smart manufacturing, further reinforces the view that operator involvement in AI decision loops is not merely desirable but operationally necessary for complex and safety-critical production environments.

2.5. Bibliometric Analysis as a Research Mapping Methodology

Bibliometric analysis has established itself as a rigorous and replicable methodology for mapping the intellectual structure, growth trajectories, and thematic evolution of research fields. Donthu et al. (2021) provide a comprehensive guide to bibliometric methods, distinguishing between performance analysis (publication and citation metrics) and science mapping (co-authorship networks, co-citation analysis, keyword co-occurrence). Moral-Muñoz et al. (2020) demonstrate the value of software tools, particularly VOSviewer and Bibliometrix (R), for producing reproducible, visually interpretable cluster maps of large bibliographic datasets.

In the context of Industry 4.0, several bibliometric studies have provided foundational mappings. Muhuri et al. (2019) conducted the first comprehensive bibliometric overview of Industry 4.0 research using Scopus. Adithya et al. (2025) extend this analysis to 2024 with a focus on smart factories and sustainability. The specific domain of AI/ML as a process optimization driver was mapped by Mateo and Redchuk (2021), whose findings of absent IIoT and operator dimensions form the direct baseline for the present study. This study contributes to the bibliometric literature on Industry 4.0 by providing the first systematic longitudinal comparison of keyword cluster evolution in the AI/ML–process optimization subfield over the 2020–2026 period.

3. Materials and Methods

3.1. Research Design

This study adopts a quantitative bibliometric research design to systematically map and evaluate the scientific literature on AI/ML-based process optimization within the context of Industry 4.0 and Industry 5.0. The methodological framework follows established bibliometric guidelines proposed by Donthu et al. (2021) and extends the work of Mateo and Redchuk (2024), who highlighted the limited visibility of IIoT and industrial operator dimensions within the AI/ML-driven process optimization literature.

A longitudinal comparative approach was employed using publications indexed in Dimensions.ai from 2020 to 2026. This period was selected to capture the accelerated growth of AI-enabled manufacturing research following the widespread adoption of digital transformation initiatives and the emergence of Industry 5.0, which emphasizes human-centricity, resilience, and sustainability (Breque et al., 2021). The comparative design enables an assessment of whether the research gaps identified by Mateo and Redchuk (2024), particularly the underrepresentation of IIoT and industrial operators, have been addressed in the evolving literature.

The bibliometric workflow consisted of five sequential stages. First, relevant search strategies were developed based on keywords associated with AI/ML, process optimization, IIoT, and industrial operators. Second, retrieved records were screened according to predefined inclusion and exclusion criteria following the PRISMA 2020 framework (Page et al., 2021). Third, bibliometric performance indicators, including publication trends, leading authors, countries, institutions, and journals, were analyzed. Fourth, science mapping techniques were conducted using VOSviewer 1.6.20 and Bibliometrix (R) to examine keyword co-occurrence networks, thematic structures, collaboration patterns, and thematic evolution. Finally, the resulting knowledge structure was compared with the baseline findings reported by Mateo and Redchuk (2024) to identify emerging themes, unresolved research gaps, and future research opportunities related to the integration of AI/ML, IIoT, and industrial operators in smart manufacturing environments. Figure 1 presents the overall research workflow and the PRISMA-based document selection process.

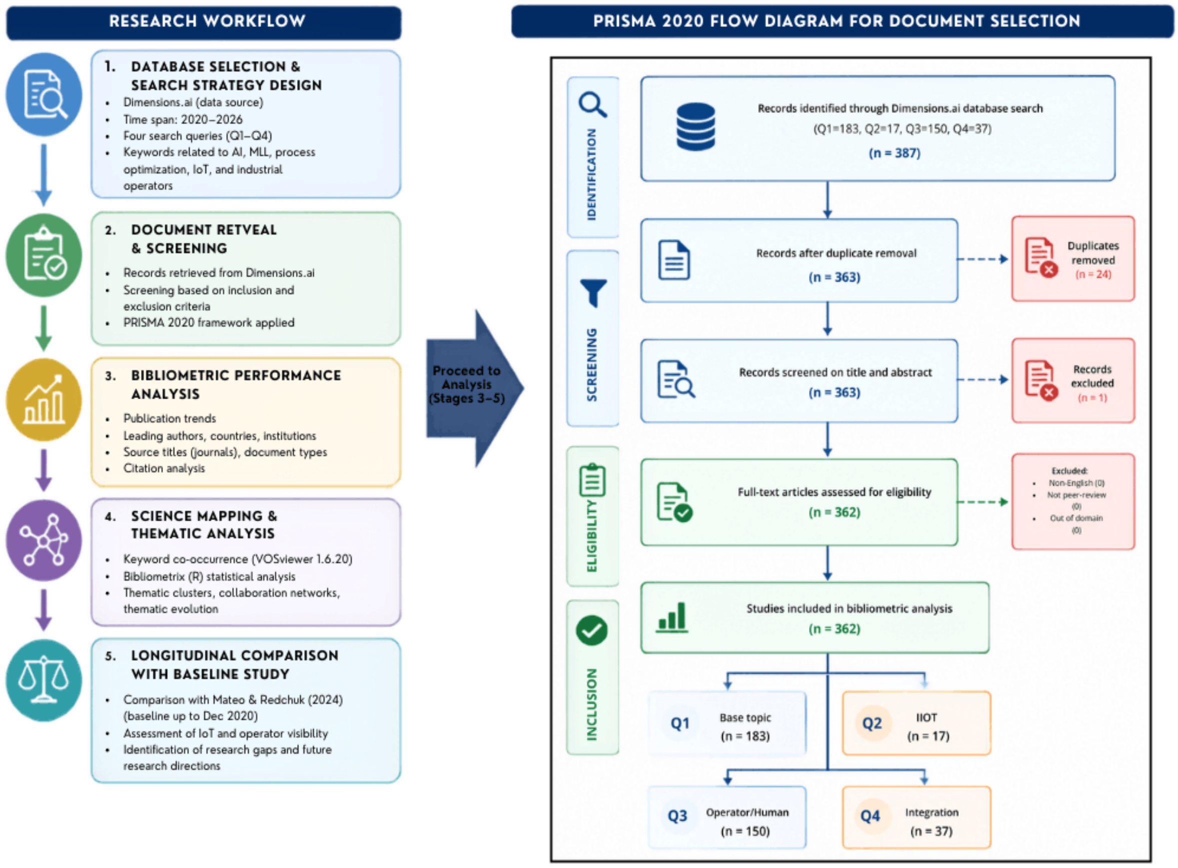

Figure 1: Research workflow and PRISMA 2020 document selection process used in the bibliometric analysis of AI/ML, IIoT, and industrial operator research within Industry 4.0 and Industry 5.0 (2020–2026)

3.2. Data Source

Dimensions.ai (Digital Science) was selected as the primary bibliographic database for this study because it provides broad coverage of scholarly publications, including journal articles, conference proceedings, books, and other research outputs. The platform also provides integrated citation and research analytics, making it suitable for bibliometric studies. In addition, a substantial proportion of publications indexed in Dimensions.ai are also indexed in Scopus, facilitating comparison with the bibliometric study conducted by Mateo and Redchuk (2024). The main characteristics of the databases considered in this study are presented in Table 1.

Table 1: Characteristics of the bibliographic databases used in this study

Aspect	Dimensions.ai (Primary Database)	Scopus (Reference Baseline)
Platform	Dimensions.ai (Digital Science)	Elsevier Scopus
Database scope	Multidisciplinary publications, conference proceedings, books, and preprints	Peer-reviewed journals and conference proceedings
Coverage advantage	Broad open-access coverage and integrated research analytics	Widely used benchmark database for bibliometric studies
Search period	2020–2026	Up to December 2020
Language	English	English
Export format	CSV, RIS	CSV, BibTeX
Analysis tools	VOSviewer 1.6.20, Bibliometrix (R) 4.x	VOSviewer 1.6.11

3.3. Search Strategy

The search strategy was developed to capture publications related to AI/ML-driven process optimization while explicitly examining the roles of IIoT and industrial operators in smart manufacturing environments. Following the recommendations of Donthu et al. (2021), Boolean operators (AND, OR) were applied to the Title, Abstract, and Keywords fields within Dimensions.ai. Four complementary search queries were designed to ensure comprehensive coverage of the research domain. The search queries and their respective research focuses are summarized in Table 2.

Table 2: Search queries used for bibliographic retrieval

Query ID	Search String	Research Focus
Q1	("artificial intelligence" OR "machine learning") AND ("process optimization") AND ("industry 4.0" OR "smart manufacturing")	Core AI/ML-based process optimization literature
Q2	("IIoT" OR "Industrial Internet of Things") AND ("machine learning" OR "artificial intelligence") AND ("process optimization" OR "process control") AND ("industry 4.0" OR "smart manufacturing")	IIoT as an AI/ML enabler in manufacturing
Q3	("operator" OR "shop floor" OR "human factor" OR "Operator 4.0" OR "human-in-the-loop") AND ("artificial intelligence" OR "machine learning") AND ("industry 4.0" OR "smart manufacturing") AND ("process")	Human operator involvement in AI/ML-enabled manufacturing
Q4	("operator") AND ("IIoT" OR "Industrial Internet of Things") AND ("machine learning" OR "artificial intelligence")	Integration of operator, IIoT, and AI/ML dimensions

After document retrieval, all records were exported and processed using Bibliometrix (R) for data cleaning and deduplication. Duplicate publications retrieved through multiple search queries were removed, and the remaining records were merged into a single analytical corpus. The final dataset was subsequently analyzed using VOSviewer and Bibliometrix to investigate publication trends, collaboration networks, thematic structures, and the evolution of research themes related to AI/ML, IIoT, and industrial operators.

3.4. Inclusion and Exclusion Criteria

Document screening was conducted following the PRISMA 2020 guidelines proposed by Page et al. (2021). The screening process aimed to ensure that only publications directly relevant to AI/ML-driven process optimization, IIoT, and industrial operator research within manufacturing environments were included in the final bibliometric corpus. The inclusion and exclusion criteria applied throughout the screening process are presented in Table 3.

Table 3: Inclusion and exclusion criteria for document selection

Criterion	Inclusion Criteria	Exclusion Criteria	Rationale
Publication period	Publications published between 2020 and 2026	Publications published before 2020	Captures the most recent phase of AI/ML, IIoT, Industry 4.0, and Industry 5.0 research, including post-pandemic digital transformation and human-centric manufacturing developments.
Language	Publications indexed with English titles, abstracts, and keywords	Records without English bibliographic information	Ensures consistency in keyword extraction, co-occurrence analysis, and thematic mapping.
Document type	Peer-reviewed journal articles	Editorials, letters, notes, errata, book reviews, theses, and non-peer-reviewed documents	Ensures scientific quality, methodological rigor, and citation reliability.
Research domain	Manufacturing, smart manufacturing, industrial engineering, Industry 4.0, Industry 5.0, and production systems	Healthcare, agriculture, finance, education, retail, logistics, and other non-manufacturing contexts	Maintains focus on industrial process optimization and shop-floor environments.
Technology scope	Studies addressing artificial intelligence, machine learning, IIoT, process optimization, predictive maintenance, industrial analytics, or smart production systems	Studies unrelated to AI/ML-enabled industrial applications	Ensures alignment with the study objectives and search strategy.
Human and IIoT relevance	Studies addressing industrial operators, human factors, Operator 4.0, human-centered AI, human-in-the-loop systems, and/or IIoT-enabled manufacturing environments	Studies with no discussion of operator or IIoT dimensions in manufacturing contexts	Supports investigation of the research gaps identified by Mateo and Redchuk (2024).
Data availability	Records with accessible title, abstract, keywords, author information, and publication metadata	Records with incomplete or inaccessible bibliographic metadata	Ensures data completeness for bibliometric and network analyses.

Following the application of these criteria, duplicate records and irrelevant publications were removed prior to the bibliometric analysis stage.

3.5. Bibliometric Analysis Tools and Indicators

Three complementary software tools were employed to perform bibliometric performance analysis and science mapping. Each tool served a specific analytical purpose, ranging from data retrieval and preprocessing to network visualization and statistical analysis. The functions of the software used in this study are summarized in Table 4.

Table 4: Bibliometric analysis tools and their functions

Tool	Version	Primary Function	Key Output
Dimensions.ai	2025	Bibliographic data retrieval and preliminary analytics	Metadata dataset (CSV/RIS)
VOSviewer	1.6.20	Keyword co-occurrence analysis, co-authorship networks, and visualization	Network maps and thematic clusters
Bibliometrix (R)	4.x	Bibliometric performance analysis and science mapping	Author, journal, country, and institution metrics
Microsoft Excel	Microsoft 365	Data summarization and visualization	Publication trends and comparative charts

The analysis focused on several commonly reported bibliometric indicators, including annual publication growth, author productivity, country and institutional contributions, journal performance, collaboration patterns, and keyword co-occurrence relationships. In addition, thematic evolution and temporal overlay analyses were conducted to examine the emergence and development of IIoT-, operator-, and AI/ML-related themes over time.

3.6. Longitudinal Comparative Framework

A key contribution of this study is the longitudinal comparison between the knowledge structure reported by Mateo and Redchuk (2024) and the updated literature landscape identified from publications published between 2020 and 2026. The comparison was designed to determine whether the previously identified gaps related to IIoT and industrial operators have evolved into established research themes within the AI/ML-driven process optimization literature. The comparative analysis was conducted across three dimensions. First, cluster continuity was examined to determine whether the thematic structures identified in the baseline study remained stable, expanded, merged, or fragmented over time. Second, gap emergence analysis assessed the visibility and relative importance of IIoT, operator, and human-factor-related keywords within the updated co-occurrence network. Third, thematic emergence analysis was performed to identify new research themes associated with Industry 5.0, sustainability, human-centered AI, and human-in-the-loop manufacturing. To support this analysis, temporal overlay visualization and keyword clustering techniques available in VOSviewer were applied to the final bibliographic dataset, enabling the identification of thematic evolution patterns and emerging research directions.

4. Results and Discussion

4.1. Document Retrieval and PRISMA Screening

The four Dimensions.ai queries collectively retrieved 387 records. After automated deduplication, 363 unique records were retained. One additional record was excluded due to an absent abstract, yielding a final analytical corpus of n = 362 peer-reviewed articles. Figure 2 presents the PRISMA 2020 flow diagram documenting this process. Query Q1 (base topic: AI/ML, process optimization, and Industry 4.0) contributed the largest share with 183 records, confirming sustained growth in the foundational theme. Q3 (operator/human factor dimension) retrieved 150 records, the second largest share constituting 41.4% of the final corpus and representing a significant increase relative to the complete absence of operator-related terms in the keyword clusters reported by Walas Mateo and Redchuk (2022) for the pre-2021 period. Q4 (three-dimension integration: Operator, IIoT, and AI/ML) retrieved 37 records, and Q2 (IIoT-specific) retrieved 17 records, indicating that while both gap dimensions are now present in the literature, the IIoT-specific dimension remains comparatively sparse.

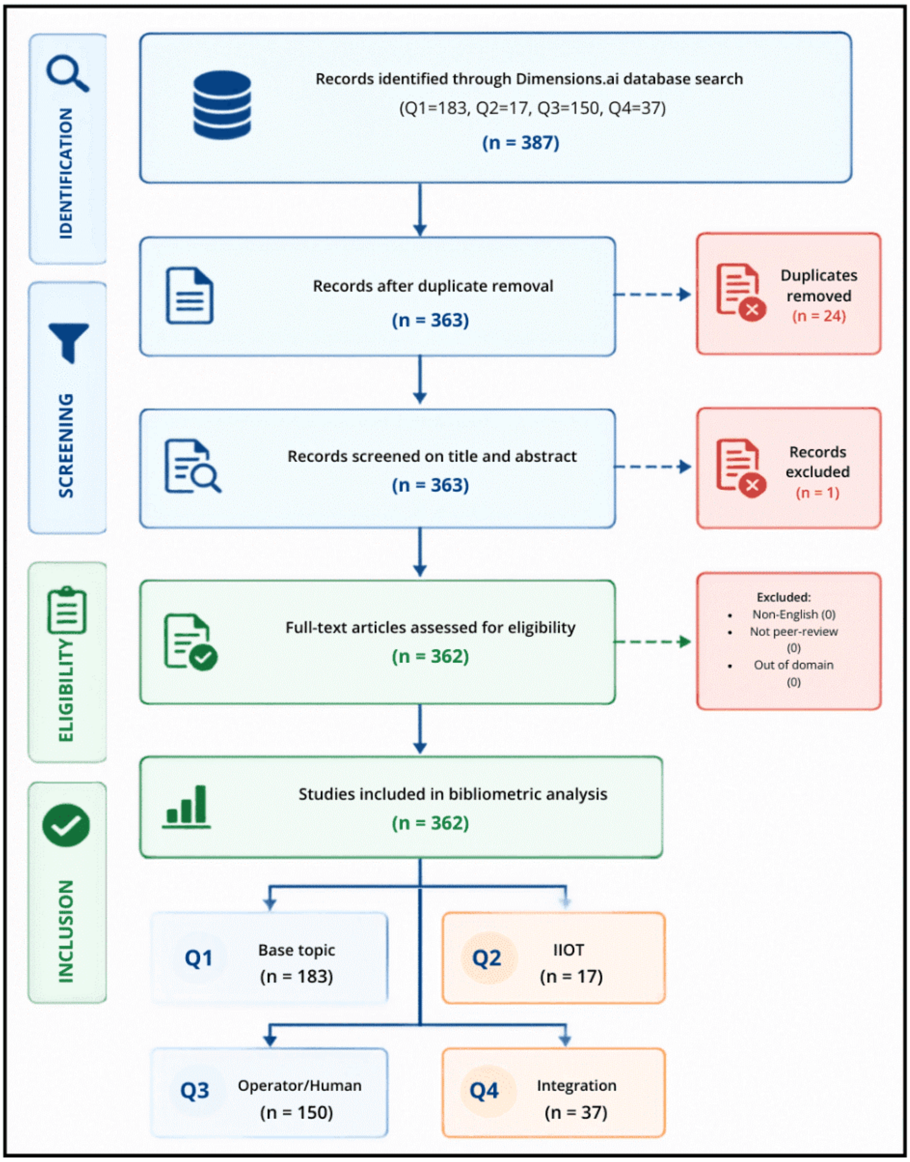

Figure 2: PRISMA 2020 flow diagram for document identification, screening, eligibility, and inclusion across four Dimensions.ai queries (2020–2026, n = 362)

4.2. Annual Publication Trends (2020–2026)

Figure 3 presents the annual publication trends for the full corpus and by query dimension. The overall trend exhibits consistent growth across the study period, with total document counts rising from 22 in 2020 to 60 in 2026 (partial year data), and reaching a peak of 117 in 2025. The cumulative corpus increases from 22 documents in 2020 to 362 by the end of the study period, representing a compound annual growth rate (CAGR) of approximately 58%. This trajectory confirms the exponential growth pattern identified by Walas Mateo and Redchuk (2022) for the pre-2021 period and demonstrates its continuation and acceleration through 2025.

Three sub-periods are discernible in the trend data. The period 2020–2022 (n = 86, 23.8% of corpus) represents the baseline phase, corresponding to the post-pandemic acceleration of digitalization and the emergence of Industry 5.0 discourse. The period 2023–2024 (n = 100, 27.6%) marks a consolidation phase in which the human-centric AI and IIoT literature began to mature. The period 2025–2026 (n = 177, 48.9%) represents a peak phase, with 2025 alone accounting for 32.3% of all retrieved documents, driven by the rapid scaling of Generative AI and Large Language Model applications in manufacturing contexts (Bajestani et al., 2026) and the operationalization of Industry 5.0 frameworks in national industrial strategies.

The query-level trend (Figure 3b) reveals an important divergence. Q1 (base topic) and Q3 (operator dimension) account for the dominant share of annual growth, while Q2 (IIoT-specific) and Q4 (three-dimension integration) remain consistently lower in absolute volume despite increasing in 2025–2026. This pattern provides initial evidence that the operator dimension has gained traction more rapidly than the IIoT-specific dimension, though neither has reached proportional representation relative to the base topic.

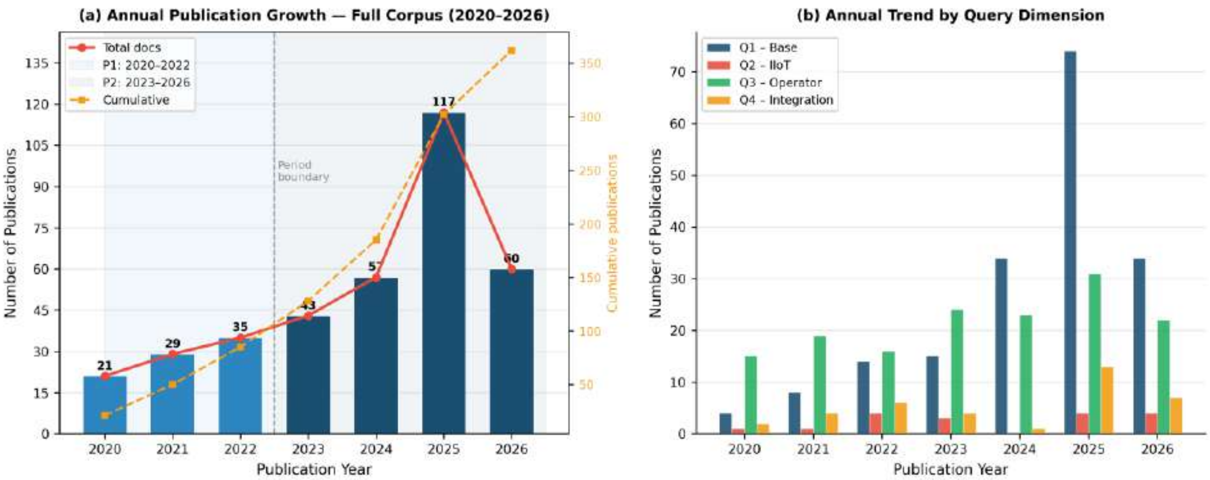

Figure 3: Annual publication growth for the full corpus (a) and by query dimension (b), 2020–2026. P1 = Period 1 (2020–2022); P2 = Period 2 (2023–2026). Dashed line in (a) represents the cumulative publication count (right axis)

4.3. Bibliometric Performance Analysis

The bibliometric performance analysis provides insights into the productivity patterns of authors, countries, journals, and citation dynamics within the AI/ML–IIoT–operator research domain. Figure 4 presents the most productive authors and countries in the deduplicated corpus. Among individual researchers, Redchuk, Andrés emerged as the most productive author with three publications, followed by Liou, Frank with three publications and Walas Mateo, Federico with two publications. The prominence of Redchuk and Walas Mateo is noteworthy because they authored the foundational bibliometric study that originally identified the limited visibility of IIoT and industrial operators within AI/ML-driven process optimization research. Their continued contribution to the field, including empirical studies investigating IIoT–machine learning integration in manufacturing environments, suggests an ongoing effort to address these previously identified research gaps. Nevertheless, the relatively low publication counts among the leading authors indicate that the field remains fragmented and characterized by limited author specialization, reflecting the emerging nature of research at the intersection of AI/ML, IIoT, and human-centered manufacturing.

At the country level, the United States dominated scientific production with 44 document contributions, followed by India (30), China (27), Germany (21), and Italy (15). Canada and the United Kingdom each contributed 14 publications, while Spain (13), Taiwan (12), and Brazil (11) completed the top-producing countries. This distribution reflects the continued leadership of North America, Europe, and Asia in AI-related manufacturing research, consistent with broader trends reported in the Industry 4.0 literature. The strong representation of Germany, Italy, and Spain may also be associated with the influence of the European Industry 5.0 agenda, which promotes human-centric, resilient, and sustainable manufacturing systems (Breque et al., 2021). In contrast, the limited participation of countries from Latin America, Africa, and Southeast Asia suggests that manufacturing perspectives from developing regions remain underrepresented, highlighting a persistent geographical imbalance within the literature. The productivity distributions of authors and countries are illustrated in Figure 4.

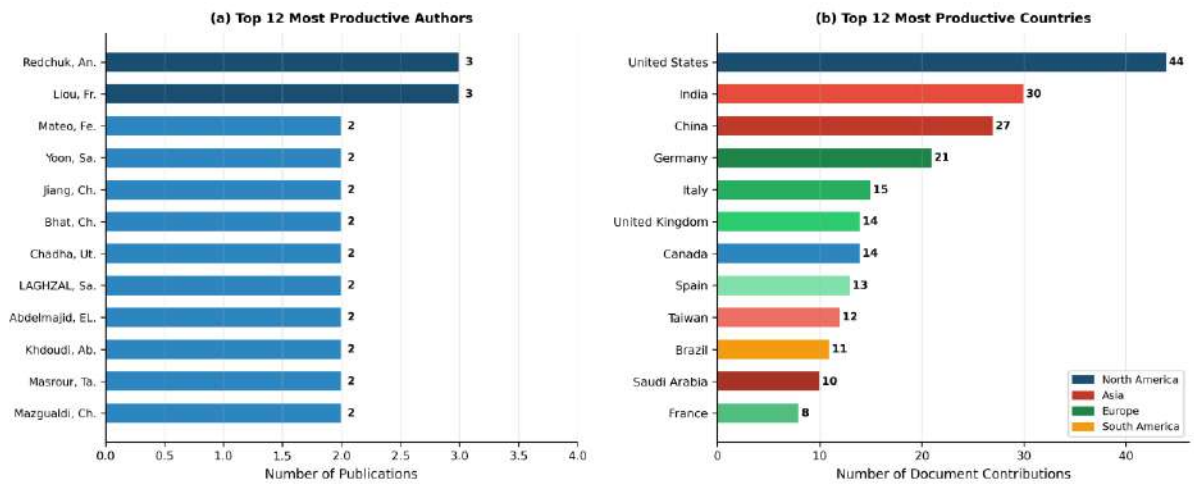

Figure 4: Top 12 most productive authors (a) and countries (b) in the deduplicated corpus (2020–2026, n = 362)

Further insights into publication performance are provided in Figure 5, which presents the most productive journals and citation patterns across publication years. The International Journal of Advanced Manufacturing Technology ranked first with 17 publications, confirming its central role as a leading outlet for research on AI-enabled manufacturing systems. Sensors followed with 14 publications, reflecting the growing importance of IIoT infrastructure, sensing technologies, and data acquisition systems within smart manufacturing environments. Other influential journals included the Journal of Intelligent Manufacturing, Applied Sciences, and the Journal of Manufacturing Systems. The diversity of publication venues demonstrates the interdisciplinary nature of the field, which integrates manufacturing engineering, industrial informatics, artificial intelligence, and human-centered production systems.

Citation analysis further reveals the intellectual impact and maturation of the research domain. Publications from 2020 recorded the highest average citations per article, largely due to highly cited review papers that established foundational knowledge in AI-driven manufacturing. Although more recent publications have had less time to accumulate citations, the total citation count increased substantially between 2020 and 2024, indicating strong and sustained scholarly interest. Notably, publications from 2024 accumulated more than three thousand citations despite their recent publication dates, suggesting rapid knowledge diffusion and growing research activity. The most cited documents in the corpus were comprehensive review articles focusing on machine learning applications in additive manufacturing and intelligent production systems, highlighting the continued importance of review-based knowledge synthesis in shaping future research directions.

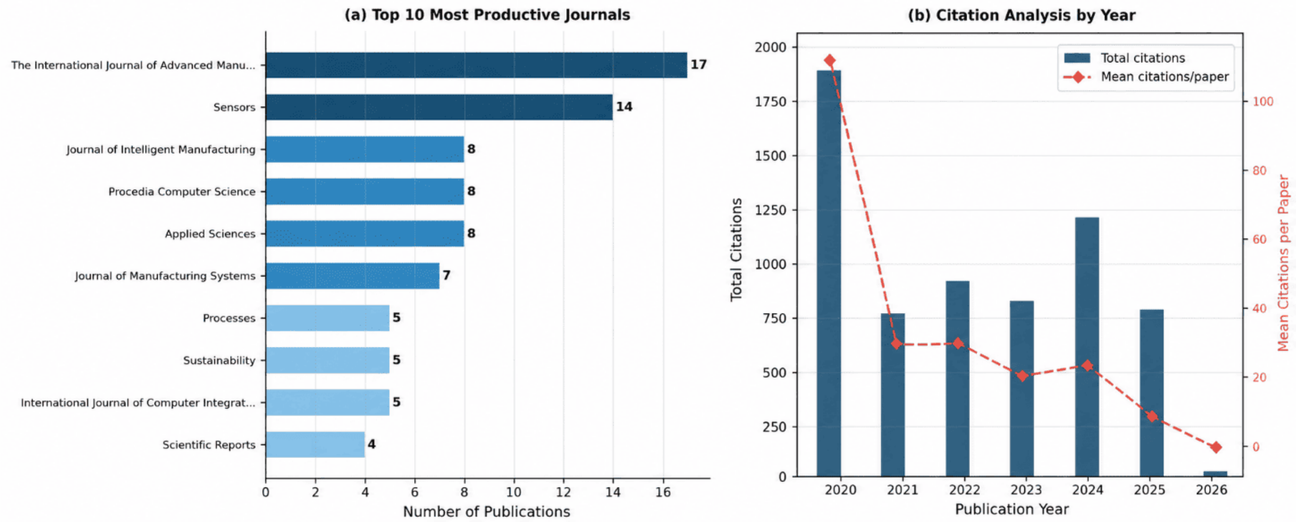

Figure 5: Top 10 most productive journals (a) and citation analysis by year (b) for the full corpus (2020–2026, n = 362)

4.4. Science Mapping: Keyword Co-occurrence Analysis

Science mapping was performed using keyword co-occurrence analysis in VOSviewer 1.6.20 to identify the thematic structure and intellectual organization of the AI/ML-driven process optimization literature. Figure 6 presents the keyword co-occurrence network generated from the final corpus using a minimum occurrence threshold of five keywords. The analysis revealed six major thematic clusters that represent the principal research streams within the field. The largest cluster is centered on artificial intelligence and smart factory technologies, including machine learning, artificial intelligence, deep learning, and digital twin. The strong connectivity among these keywords confirms that AI-based technologies remain the dominant foundation of industrial process optimization research. The presence of digital twin as a highly connected node suggests its increasing importance as a technological bridge between physical manufacturing systems and AI-driven decision support. A second cluster focuses on smart manufacturing and production integration, incorporating themes such as automation, manufacturing processes, quality control, and sustainability. The appearance of sustainability-related keywords reflects the growing influence of Industry 5.0 and the shift toward more resilient and human-centered manufacturing systems.

A third cluster is organized around cyber-physical systems, IoT, and IIoT technologies. Unlike the findings reported by Mateo and Redchuk (2024), where IIoT was not identified as a prominent thematic construct, the current analysis shows IIoT emerging as a distinct keyword connected to cyber-physical systems, edge computing, sensors, and industrial data infrastructure. This finding indicates that IIoT has become increasingly visible within the AI/ML manufacturing literature and is gradually establishing its own thematic identity. Additional clusters encompass strategic and knowledge-management themes as well as methodological and analytical approaches, both of which remain important supporting components of the research domain.

Most notably, the analysis identified an emerging cluster associated with industrial operators and human-centered manufacturing. This cluster includes keywords such as operator, human factor, Operator 4.0, human-in-the-loop, collaborative robot, and human-centered AI. The presence of this cluster provides direct bibliometric evidence that human-related dimensions, which were largely absent in earlier studies, are becoming increasingly recognized within the literature. Nevertheless, the relatively smaller node sizes and weaker network connections compared with the dominant AI and smart manufacturing clusters suggest that research on industrial operators remains in an emerging stage rather than a mature thematic area.

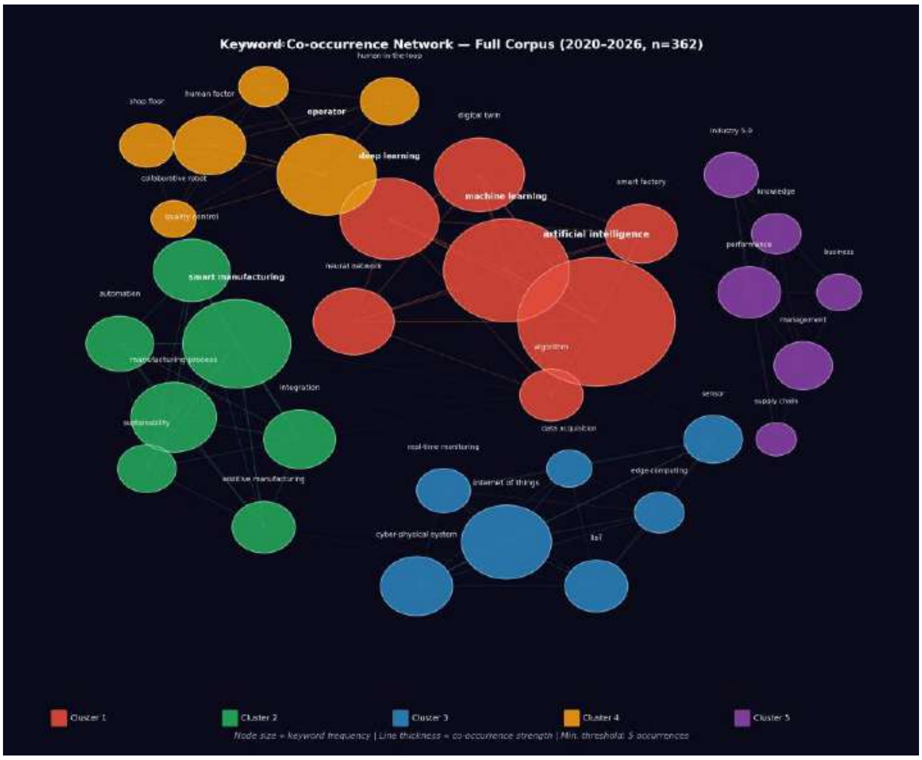

Figure 6: Keyword co-occurrence network for the full corpus (2020–2026, n = 362), generated using VOSviewer 1.6.20, node size represents keyword frequency, while link strength represents co-occurrence intensity among keywords

To further investigate thematic evolution, a longitudinal comparison was conducted between two periods: 2020–2022 and 2023–2026. The results, presented in Figure 7, reveal that the principal thematic structure of the field has remained relatively stable over time, with the AI and smart factory cluster continuing to dominate both periods. However, notable changes are observed in the IIoT and operator dimensions. The relative prominence of IIoT-related keywords increased substantially during the second period, indicating growing scholarly attention toward industrial connectivity, edge computing, and data-driven manufacturing infrastructures. Although IIoT remains less dominant than core AI and smart manufacturing themes, its increased visibility suggests a gradual narrowing of the research gap identified by Mateo and Redchuk (2024).

An even stronger trend is observed for the operator and human-factor dimension. Keywords associated with Operator 4.0, human-in-the-loop systems, collaborative robotics, and human-centered AI expanded considerably during the 2023–2026 period, reflecting the influence of Industry 5.0 principles and the increasing emphasis on human–machine collaboration. This growth suggests that the literature is progressively moving beyond purely technology-centered perspectives toward more ba lanced approaches that integrate technological innovation with human expertise and decision-making. Nevertheless, the thematic weight of the operator cluster remains considerably lower than that of the dominant AI and smart manufacturing clusters, indicating that substantial opportunities for future research still exist.

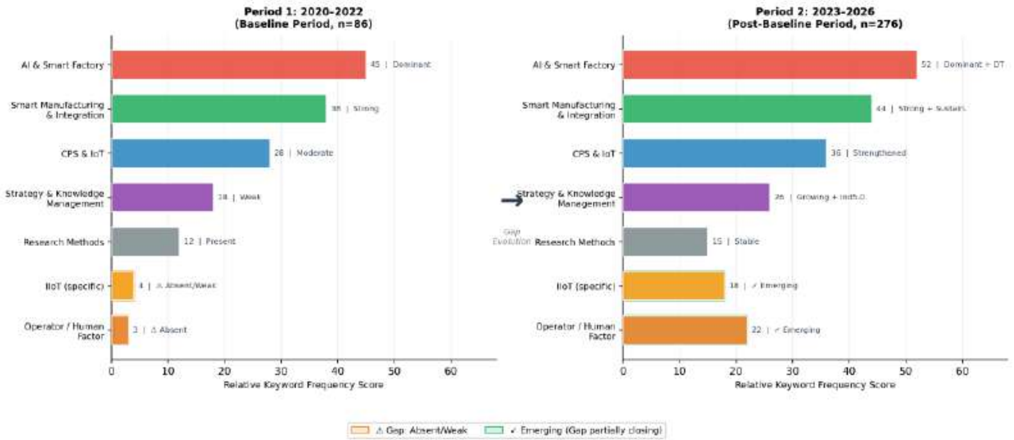

Figure 7: Longitudinal comparison of keyword cluster thematic weights between 2020–2022 and 2023–2026, highlighting the evolution of AI, IIoT, and operator-related themes within the literature

The results presented in Figures 6–7 collectively indicate that the intellectual structure of AI/ML-driven process optimization research has evolved substantially since the baseline study conducted by Mateo and Redchuk (2024). While the dominant themes identified in the earlier study remain visible, several new concepts associated with

Industry 5.0, human-centered manufacturing, and IIoT have gained increasing prominence during the 2020–2026 period. In particular, the emergence of operator-related keywords and the growing differentiation of IIoT from generic IoT terminology suggest a gradual shift toward a more integrated Operator–IIoT–AI/ML research paradigm. A comparative summary of the thematic structures identified by Mateo and Redchuk (2024) and those observed in the present study is provided in Table 5.

Table 5: Comparative summary of keyword clusters from Mateo and Redchuk (2024) and the present study (2020–2026)

Cluster Theme	Mateo & Redchuk (2024) (Scopus, n = 167, up to Dec 2020)	This Study (2020–2026) (Dimensions.ai, n = 362)	Change
AI & Smart Factory	Dominant, machine learning, algorithm, smart factory	Dominant, digital twin and generative AI vocabulary emerging	Expanded
Smart Manufacturing & Integration	Strong, integration, control, manufacturing industry	Strong, sustainability and Industry 5.0 concepts increasingly visible	Expanded
CPS & IoT	Moderate, cyber-physical system, IoT, demand, service	Strengthened, IIoT emerging as a differentiated construct within Cluster 3	Strengthened
Strategy & Knowledge Management	Weak, management, knowledge, performance, business	Growing, Industry 5.0 and HCAI concepts increasing thematic weight	Strengthened
Research Methods	Present, review, study, literature, research	Stable, increasing volume of bibliometric and review-based studies	Stable
Human Factor / Operator	Absent from all identified clusters	Emerging, operator, human factor, human-in-the-loop, Operator 4.0, collaborative robotics	Gap partially closing
IIoT (Specific Construct)	Absent as a distinct construct; represented only through generic IoT terminology	Emerging thematic component within the CPS/IIoT cluster with increasing keyword prominence	Gap partially closing

As shown in Table 5, the most significant structural changes occurred in the Human Factor/Operator and IIoT dimensions. Both themes were either absent or weakly represented in the baseline study but emerged as identifiable components of the thematic structure in the 2020–2026 corpus. The appearance of keywords such as Operator 4.0, human-in-the-loop, human-centered AI, and IIoT reflects growing scholarly recognition of the importance of integrating human expertise, industrial connectivity, and AI/ML technologies within manufacturing systems. At the same time, the expansion of the AI and Smart Manufacturing clusters through digital twin, sustainability, and Industry 5.0 concepts indicates that the field is evolving beyond purely technology-driven optimization toward a broader perspective that incorporates resilience, human-centeredness, and sustainable industrial transformation. Despite these developments, the thematic prominence of IIoT and operator-related research remains lower than that of the dominant AI and Smart Manufacturing clusters, suggesting that both dimensions continue to represent important opportunities for future empirical investigation.

4.5. Discussion

The findings of this study demonstrate that research on AI/ML-based process optimization in manufacturing has entered a phase of rapid expansion and thematic diversification during the 2020–2026 period. The sustained increase in publication output observed in Figure 3 confirms the continuing momentum of Industry 4.0 research reported by Muhuri et al. (2019), Mateo and Redchuk (2024), and Adithya et al. (2025). However, unlike earlier periods in which research was primarily concentrated on automation, cyber-physical systems, and data-driven optimization, the present corpus reveals increasing attention to Industry 5.0 concepts, particularly sustainability, resilience, and human-centric manufacturing. This evolution suggests that the focus of manufacturing research is gradually shifting from technology deployment alone toward the integration of technological, organizational, and human dimensions.

The bibliometric performance analysis further indicates that the field remains relatively fragmented despite its rapid growth. The most productive authors identified in this study contributed only a small number of publications, suggesting that no single research group currently dominates the operator–IIoT–AI/ML domain. This finding is consistent with the observations of Donthu et al. (2021), who noted that emerging interdisciplinary research fields often exhibit dispersed authorship patterns before reaching thematic maturity. At the country level, the dominance of the United States, China, India, and several European countries reflects broader global patterns of Industry 4.0 research investment (Adithya et al., 2025). The comparatively limited representation of developing regions highlights a persistent geographical imbalance and suggests that future research should investigate how AI/ML-enabled manufacturing is being adopted in emerging industrial economies.

One of the most important findings concerns the evolution of IIoT as a thematic construct within the literature. Mateo and Redchuk (2024) reported that IIoT did not emerge as a significant keyword despite its recognized importance in enabling AI-driven process optimization. The present study demonstrates that this situation has changed. IIoT now appears as a distinguishable component of the cyber-physical systems cluster and exhibits substantial growth during the 2023–2026 period. This trend is consistent with the technological developments described by Frankó et al. (2022) and Wang et al. (2024), who emphasized the growing role of connected sensors, edge computing, and industrial data infrastructures in supporting intelligent manufacturing systems. Nevertheless, the relatively modest thematic weight of IIoT compared with the dominant AI and smart manufacturing clusters suggests that industrial connectivity continues to be treated primarily as an enabling infrastructure rather than as an independent research focus.

An even more significant development is the emergence of the human factor and operator dimension. Earlier bibliometric studies found little evidence that industrial operators were being considered within AI-driven process optimization research (Mateo & Redchuk, 2024). In contrast, the current analysis identifies a dedicated cluster containing keywords such as Operator 4.0, human factor, human-in-the-loop, collaborative robotics, and human-centered AI. This finding aligns closely with the conceptual arguments advanced by Romero et al. (2016), Cunha et al. (2022), and Mentzas et al. (2024), who argued that future manufacturing systems should emphasize collaboration between humans and intelligent technologies rather than worker replacement. The growing visibility of these concepts also reflects the influence of the Industry 5.0 framework introduced by the European Commission (Breque et al., 2021), which places human well-being and societal value alongside productivity and efficiency objectives.

The longitudinal analysis provides additional evidence that the intellectual structure of the field is evolving toward a more integrated perspective. While AI and smart manufacturing remain the dominant research themes, the increasing visibility of both IIoT and operator-related concepts suggests that the literature is gradually converging toward a triadic framework in which intelligent algorithms, connected industrial infrastructures, and human expertise operate as complementary elements of process optimization. This observation is supported by empirical studies such as Redchuk et al. (2023), which demonstrated measurable operational benefits from the combined deployment of IIoT technologies, machine learning models, and human decision-making in manufacturing environments. The emergence of such integrated approaches indicates that future competitive advantages may arise not from AI technologies alone but from the effective orchestration of AI, connectivity, and human knowledge.

Despite these advances, the results also reveal that the two research gaps identified by Mateo and Redchuk (2024) have not been fully resolved. Although both IIoT and operator-related themes have become more visible, their thematic prominence remains substantially lower than that of the dominant AI and smart manufacturing clusters. This suggests that existing studies continue to prioritize algorithmic performance, automation, and technical implementation over investigations of socio-technical integration. Consequently, future research should focus on empirical assessments of human–AI collaboration, operator trust in AI systems, explainable industrial AI, IIoT governance, and the organizational implications of Industry 5.0 adoption. Such research would contribute to a more comprehensive understanding of how intelligent manufacturing systems can achieve not only operational efficiency but also sustainability, resilience, and human-centered value creation.

This study is subject to several limitations. First, the analysis was restricted to English-language journal articles indexed through Dimensions.ai, potentially excluding relevant contributions published in other languages or dissemination formats. Second, bibliometric methods capture the structure of scientific knowledge but cannot directly evaluate the practical effectiveness of specific technologies or implementation strategies. Third, the relatively recent nature of Industry 5.0-related publications may have limited their citation accumulation and visibility within the network structure. Future studies could address these limitations by incorporating multiple databases, including conference proceedings, and combining bibliometric approaches with systematic literature reviews or empirical case studies to provide deeper insights into the evolving Operator–IIoT–AI/ML ecosystem.

5. Conclussion

This study analyzed the evolution of AI/ML-based process optimization research in the context of Industry 4.0 and Industry 5.0 using a bibliometric approach applied to publications indexed in Dimensions.ai from 2020 to 2026. The results demonstrate a sustained increase in scientific output, reflecting the growing importance of intelligent technologies in manufacturing environments. The knowledge structure of the field remains centered on AI, machine learning, smart manufacturing, and cyber-physical systems, confirming the continued dominance of technology-driven process optimization research.

The keyword co-occurrence analysis identified six thematic clusters, indicating that the research domain has become more diverse and interdisciplinary. In addition to the established themes of AI, smart manufacturing, and industrial integration, the analysis revealed increasing attention to IIoT, sustainability, Industry 5.0, and human-centered manufacturing concepts. Longitudinal analysis showed that IIoT has evolved from a peripheral concept into a recognizable thematic component within the manufacturing literature, while operator-related concepts such as Operator 4.0, human-in-the-loop systems, and human-centered AI have emerged as a distinct research theme. These findings indicate a gradual shift toward a more integrated manufacturing paradigm that combines intelligent algorithms, industrial connectivity, and human participation.

The comparative analysis further showed that the thematic structure reported in earlier studies remains largely intact but has expanded through the incorporation of new concepts associated with Industry 5.0. The increasing visibility of IIoT and operator-related themes suggests that the research community is paying greater attention to the interaction between technological and human dimensions of manufacturing systems. Nevertheless, both themes remain less prominent than the dominant AI and smart manufacturing clusters, indicating that they are still developing areas within the broader research landscape.

This study is limited by its reliance on a single bibliographic database, its focus on English-language journal articles, and the inherent constraints of bibliometric methods, which describe patterns of scientific production rather than practical implementation outcomes. Future research should complement bibliometric analyses with systematic literature reviews, empirical case studies, and cross-database investigations to further explore how AI/ML, IIoT, and human-centered approaches can be integrated to support sustainable, resilient, and intelligent manufacturing systems.

References

Adithya, M. A., Geetha, R., Sundar, S., Varghese, M. A., & Velmurugan, P. R. (2025). Bibliometric analysis of the evolution of smart factories and sustainable manufacturing in Industry 4.0. *Discover Sustainability*, *6*(1), 1179.

Bajestani, M. S., Mun, D., & Kim, D. B. (2026). Human-in-the-loop and large language models in smart manufacturing: Current applications, challenges, and perspectives. *Journal of Manufacturing Systems*, *86*, 913-941.

Barua, D. A., Sami, S. A., & Barua, L. (2025). Leveraging artificial intelligence for smart production management in industry 4.0. *Scientific Reports*, *15*(1), 41559.

Breque, M., De Nul, L., & Petridis, A. (2021). *Industry 5.0: towards a sustainable, human-centric and resilient European industry* (No. KI-BD-20-021-EN-N). Directorate General for Research and Innovation (DG RTD) of the European Commission.

Cunha, L., Silva, D., & Maggioli, S. (2022). Exploring the status of the human operator in Industry 4.0: A systematic review. *Frontiers in Psychology*, *13*, 889129.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of business research*, *133*, 285-296.

Erozan, İ. (2019). A fuzzy decision support system for managing maintenance activities of critical components in manufacturing systems. *Journal of Manufacturing Systems*, *52*, 110-120.

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International journal of production economics*, *210*, 15-26.

Frankó, A., Hollósi, G., Ficzere, D., & Varga, P. (2022). Applied machine learning for IIOT and smart production—Methods to improve production quality, safety and sustainability. *Sensors*, *22*(23), 9148.

Ghahramani, M., Qiao, Y., Zhou, M. C., O'Hagan, A., & Sweeney, J. (2020). AI-based modeling and data-driven evaluation for smart manufacturing processes. *IEEE/CAA Journal of Automatica Sinica*, *7*(4), 1026-1037.

Iansiti, M., & Lakhani, K. (2020). *Competing in the age of AI: Strategy and leadership when algorithms and networks run the world*. Harvard Business Review Press.

Ibarra, D., Ganzarain, J., & Igartua, J. I. (2018). Business model innovation through Industry 4.0: A review. *Procedia manufacturing*, *22*, 4-10.

Kang, Z., Catal, C., & Tekinerdogan, B. (2020). Machine learning applications in production lines: A systematic literature review. *Computers & Industrial Engineering*, *149*, 106773.

Mateo, F. W., & Redchuk, A. (2024). Artificial Intelligence as a Process Optimization driver under industry 4.0 framework and the role of IIoT, a bibliometric analysis. *Journal of Industrial Integration and Management*, *9*(03), 357-372.

Mateo, F.W, Redchuk, A., & Tornillo, J. E. (2021). IIoT/IoT and artificial intelligence/machine learning as a process optimization driver under Industry 4.0 model. Journal of Computer Science and Technology, *21*(2), 1–12.

Mentzas, G., Hribernik, K., Stahre, J., Romero, D., & Soldatos, J. (2024). human-centered artificial intelligence in industry 5.0. *Frontiers in Artificial Intelligence*, *7*, 1429186.

Merediz-Solà, I., & Bariviera, A. F. (2019). A bibliometric analysis of bitcoin scientific production. *Research in International Business and Finance*, *50*, 294-305.

Moral-Muñoz, J. A., Herrera-Viedma, E., Santisteban-Espejo, A., & Cobo, M. J. (2020). Software tools for conducting bibliometric analysis in science: An up-to-date review. El Profesional de la Información, 29(1). https://doi.org/10.3145/epi.2020.ene.03

Muhuri, P. K., Shukla, A. K., & Abraham, A. (2019). Industry 4.0: A bibliometric analysis and detailed overview. *Engineering applications of artificial intelligence*, *78*, 218-235.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Porter, M. E., & Heppelmann, J. E. (2015). How smart, connected products are transforming companies. *Harvard business review*, *93*(10), 96-114.

Redchuk, A., Mateo, F.W, Pascal, G., & Tornillo, J. E. (2023). Adoption case of IIoT and machine learning to improve energy consumption at a process manufacturing firm, under Industry 5.0 model. *Big Data and Cognitive Computing*, *7*(1), 42.

Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å., & Gorecky, D. (2016, October). Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. In *proceedings of the international conference on computers and industrial engineering (CIE46), Tianjin, China* (pp. 29-31).

Ruiz-Sarmiento, J. R., Monroy, J., Moreno, F. A., Galindo, C., Bonelo, J. M., & Gonzalez-Jimenez, J. (2020). A predictive model for the maintenance of industrial machinery in the context of industry 4.0. *Engineering Applications of Artificial Intelligence*, *87*, 103289.

Samuels, A. (2025). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: a systematic literature review. *Frontiers in artificial intelligence*, *7*, 1477044.

Wang, X., Hu, H., Wang, Y., & Wang, Z. (2024). IoT real-time production monitoring and automated process transformation in smart manufacturing. *Journal of Organizational and End User Computing (JOEUC)*, *36*(1), 1-25.