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EMERGING TRENDS IN ARTIFICIAL INTELLIGENCE (AI) -DRIVEN OPERATIONS: A BIBLIOMETRIC ANALYSIS

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EMERGING TRENDS IN ARTIFICIAL INTELLIGENCE (AI) -DRIVEN OPERATIONS: *A BIBLIOMETRIC ANALYSIS*

Abstract

Background

Artificial Intelligence (AI) has become a transformative force in operational domains, reshaping processes in manufacturing, logistics, scheduling, and cloud-based systems. The rapid proliferation of research output, particularly within the 2025–2026 period, underscores the need for a systematic bibliometric assessment to elucidate emerging thematic trajectories, intellectual structures, and influential contributors in AI-driven operations.

Methods

A quantitative bibliometric design was employed using the Biblioshiny platform, underpinned by the Bibliometrix R package. Bibliographic data were sourced from Scopus and restricted to publications dated 2025–2026 that explicitly addressed AI applications in operational contexts. The analysis integrated performance indicators such as publication productivity and citation impact with science mapping techniques, including co-authorship analysis, keyword co-occurrence, thematic clustering, and network centrality metrics.

Results

Findings reveal a pronounced temporal concentration of publications in 2025, indicative of a hyper-accelerated research front. China emerged as the predominant contributor, with South China University of Technology and other leading institutions demonstrating the highest output. Thematic mapping identified three major clusters reinforcement learning, scheduling algorithms, and smart manufacturing and a smaller emergent cluster on fabrication. Strong inter-thematic linkages highlight the convergence of AI methodologies with operational optimization and Industry 4.0 applications. Owing to the recency of the dataset, traditional citation counts were minimal; thus, PageRank and network-based metrics provided more meaningful indicators of early influence. Several recent publications demonstrated notable structural impact within the emerging knowledge network.

Conclusion

AI-driven operations research is characterized by rapid expansion, thematic convergence, and significant regional concentration, particularly within Chinese institutions. Reinforcement learning, scheduling algorithms, and smart manufacturing constitute the intellectual core of the field, reinforced by advances in cloud and edge computing. In the context of an emergent research landscape, network-based impact measures are more appropriate than conventional citation metrics. The findings indicate a swift transition from theoretical exploration to applied innovation, necessitating continued monitoring, interdisciplinary collaboration, and strategic policy and industry engagement.

Keywords

Artificial intelligence, operations research, reinforcement learning, scheduling algorithms, smart manufacturing, bibliometric analysis.

Introduction

The integration of Artificial Intelligence (AI), particularly machine learning and deep learning, is reshaping traditional operational systems across multiple sectors (Soori, Arezoo, & Dastres, 2023). Industries such as manufacturing, logistics, supply chain management, and distributed computing increasingly rely on AI to enhance efficiency, responsiveness, and decision-making autonomy. These technologies enable intelligent scheduling, dynamic resource allocation, predictive maintenance, and automation in complex environments, including cloud infrastructures and cyber-physical systems. By embedding adaptive capabilities into operational processes, AI drives not only efficiency gains but also resilience, flexibility, and scalability in rapidly evolving industrial settings (Sundaramurthy, Ravichandran, Inaganti, & Muppalaneni, 2022).

As AI becomes more deeply embedded in operational contexts, bibliometric analysis has gained prominence as a methodological tool for mapping the structure, growth, and intellectual evolution of the field. Previous scientometric studies, such as the analysis of smart cities and sustainable development (2015–2018), have demonstrated the value of mapping intellectual structures to understand technology-driven research frontiers (Sanico, M.F., 2025). Bibliometric techniques provide a systematic framework for identifying publication trends, influential authors and institutions, collaboration networks, and emerging thematic patterns (Zucolotto, Yamane, & Siman, 2022). These analyses offer strategic insights for researchers, policymakers, and industry stakeholders seeking to monitor scientific developments, allocate resources, and identify research gaps (Skute, Zalewska-Kurek, Hatak, & de Weerd-Nederhof, 2017). In the context of rapidly advancing AI applications, bibliometric mapping enables the identification of emerging subfields with high transformative potential.

Current developments in AI-driven operations are marked by the convergence of intelligent algorithms with real-time data processing, enabling systems to operate autonomously in dynamic environments (Ekundayo, 2024). Reinforcement learning (RL) has emerged as a critical methodological approach for adaptive decision-making in domains such as logistics, scheduling, and inventory management. Its capacity for continuous learning through environmental feedback makes it well-suited to high-variability contexts. Simultaneously, the integration of AI with the Internet of Things (IoT) and cyber-physical systems has advanced the development of smart manufacturing ecosystems, where automation, data exchange, and self-optimization are central features (Dave, 2023). These technological shifts signal a transition toward predictive and prescriptive analytics as core components of next-generation operational systems.

The integration of AI into cloud-based and edge-computing infrastructures has further expanded its applicability across sectors such as healthcare, transportation, and energy (Kumar, 2022). Interdisciplinary collaboration is accelerating the development of hybrid approaches that combine classical optimization with AI-driven decision models. The increasing emphasis on explainable AI (XAI) reflects a parallel need for transparency, accountability, and ethical alignment in automated operational systems (N et al., 2024). These developments point to a rapidly evolving research landscape characterized by both technological innovation and cross-sector applicability.

Given this dynamic context, the present bibliometric study aims to provide a comprehensive and timely overview of the research landscape on AI-driven operations. Specifically, it seeks to: (1) analyze publication output and growth trajectories; (2) identify the most prolific and influential authors and institutions; (3) map dominant research themes and examine their interrelationships; and (4) highlight emergent and high-impact publications using both traditional and network-based citation metrics. By focusing on publications from 2025 to 2026, this study offers an early assessment of an accelerating research frontier and contributes to the strategic understanding of future research directions in AI-driven operational systems.

Methods

Study Design

This study employed a quantitative bibliometric research design to systematically examine the intellectual structure and thematic evolution of AI-driven operations research. Bibliometric analysis was selected for its capacity to provide objective insights into publication trends, influential entities, collaboration patterns, and emerging conceptual domains. The approach combined performance analysis—focusing on productivity and impact metrics—with science mapping techniques that reveal structural and thematic relationships within the literature. The design is exploratory and descriptive, aligned with the principles of science mapping, and aimed at capturing both the breadth and depth of scholarly activity in this rapidly developing field.

Data Source

The primary data source for this study was the Biblioshiny platform, an R-based web interface built upon the Bibliometrix package. Biblioshiny facilitates advanced bibliometric analysis and visualization, enabling the examination of metadata derived from established bibliographic databases. Scopus was selected as the source database due to its comprehensive coverage of peer-reviewed publications in engineering, computer science, technology, and related domains pertinent to AI and operations research. Extracted metadata included publication titles, authors, affiliations, keywords, source journals, citation counts, and publication years, providing a robust foundation for subsequent analyses.

Search Strategy and Data Extraction

A structured search strategy was implemented to identify relevant literature at the intersection of Artificial Intelligence and Operations Research. Boolean operators and controlled vocabulary were used to formulate the query, incorporating key terms such as “Artificial Intelligence,” “Machine Learning,” “Reinforcement Learning,” “Smart Manufacturing,” “Scheduling Algorithms,” and “Operational Optimization.” The search was limited to article titles, abstracts, and keywords to ensure thematic relevance and was restricted to publications from 2025 to 2026 to capture the emerging research front.

The search was conducted in Scopus. Retrieved documents were exported in BibTeX format and uploaded into Biblioshiny for processing. The exported metadata included essential fields for performance indicators and network-based analyses, such as author names, institutional affiliations, keyword occurrences, citation data, and source titles. Both journal articles and conference papers were retained to reflect the multidisciplinary and fast-evolving nature of the field.

Data Screening and Pre-processing

Following extraction, the dataset underwent screening to ensure relevance and data quality. Duplicate entries, incomplete records, and publications outside the scope of AI-driven operational applications were removed. Only documents explicitly addressing AI techniques applied to operational processes were retained. Editorials, errata, and non-English publications were excluded to maintain consistency and methodological rigor.

Preprocessing procedures were conducted to standardize metadata and enhance the reliability of network analyses. Author names, institutional affiliations, and keywords were normalized to address inconsistencies in spelling and formatting. Keyword harmonization was achieved through stemming and consolidation of variants (e.g., "optimising" and "optimization"). These steps were essential to minimize fragmentation and ensure accurate representation of co-authorship and keyword co-occurrence networks. The finalized dataset was then prepared for analysis within Biblioshiny.

Data Analysis

Data analysis comprised two major components: performance analysis and science mapping. Performance analysis examined publication productivity by authors, institutions, countries, and source journals, alongside citation-based metrics such as total citations, average citations per document, and h-index. Annual publication trends were also assessed to identify growth trajectories.

Science mapping techniques were employed to explore the conceptual and collaborative structure of the field. Co-authorship analysis was conducted to map collaboration networks among authors, institutions, and countries. Keyword co-occurrence analysis was used to identify dominant themes and their interconnections, while thematic evolution mapping traced shifts in research priorities over time. Visualization tools within Biblioshiny, including thematic maps, collaboration graphs, and trend topic plots, were used to support interpretation. Together, these methods yielded a comprehensive understanding of the field's structural dynamics and emergent research directions.

Results

The bibliometric dataset reveals a distinctly concentrated temporal pattern, with the majority of publications dated 2025 and extending minimally into 2026. This sharply contrasts with the cited references, which span from 1776 to 2020. This temporal asymmetry indicates that the present analysis is not retrospective but rather captures an emergent and rapidly accelerating research front. The compressed timeframe underscores the immediacy of scholarly activity in AI-driven operations and reflects the rapid pace of innovation in the field.

Author Productivity

The analysis of author contributions demonstrates a high degree of concentration among leading scholars. WANG X is the most prolific contributor with 11 articles and a fractional authorship score of 2.2714. This is followed by LI X and LI Y, each with nine publications, with fractionalized contributions of 1.8551 and 2.7095, respectively. The use of fractional authorship provides a more accurate assessment of individual contributions within multi-author publications, which are prevalent in this collaborative domain.

Table 1. Prolific Authors

Authors	Articles	Articles Fractionalized
WANG X	11	2.2714
LI X	9	1.8551
LI Y	9	2.7095
WANG L	9	1.6782
WANG Y	9	1.9119
LI H	8	1.8023
WANG J	8	1.3940
ZHANG X	8	1.3123
CHEN X	7	1.1388
LIU Y	7	1.2261
LIU Z	7	1.3190
ZHANG J	7	1.3916
ZHANG Y	7	2.1261
CHEN Y	6	1.1670
LI M	6	1.3000
ZHANG H	6	1.2713

Institutional Contributions

Institutional productivity is similarly concentrated, with Chinese universities and research institutions dominating the landscape. South China University of Technology ranks highest with 36 publications, followed by Islamic Azad University (32 articles) and Beihang University (22 articles). Additional leading contributors include Guizhou University, Guangdong University of Technology, and Wuhan University of Technology. The prominence of Chinese institutions suggests substantial national investment and research prioritization in AI-driven operational technologies. This trend highlights China's strategic positioning in advancing innovation and shaping global trajectories within this domain.

Table 2. Influential Institutions

Affiliation	**Articles**
SOUTH CHINA UNIVERSITY OF TECHNOLOGY	36
ISLAMIC AZAD UNIVERSITY	32
BEIHANG UNIVERSITY	22
GUIZHOU UNIVERSITY	19
GUANGDONG UNIVERSITY OF TECHNOLOGY	17
WUHAN UNIVERSITY OF TECHNOLOGY	17
AMERICAN COLLEGE OF CLINICAL PHARMACY	16
BEIJING UNIVERSITY OF TECHNOLOGY	16
CENTRAL SOUTH UNIVERSITY	16
UNIVERSITI PUTRA MALAYSIA	16
THE HONG KONG POLYTECHNIC UNIVERSITY	15
XI'AN JIAOTONG UNIVERSITY	15
CHONGQING UNIVERSITY	14
HUAZHONG UNIVERSITY OF SCIENCE AND TECHNOLOGY	14
TIANJIN UNIVERSITY	14

Thematic Clusters

The thematic analysis revealed four distinct research clusters, three of which form the intellectual core of the field: reinforcement learning, smart manufacturing, and scheduling algorithms, with a fourth, smaller cluster focused on fabrication. Reinforcement learning emerged as the most influential thematic hub, with 1,343 associated keywords and the highest centrality scores (Callon Centrality 12.5388, Rank Centrality 4). Frequently linked with concepts such as deep reinforcement learning, machine learning, optimisation, decision making, and artificial intelligence, this cluster reflects its foundational role in methodological innovation across operational contexts. Smart manufacturing, comprising 501 keywords, is closely associated with terms like Industry 4.0, digital twin, flexible manufacturing systems, and predictive maintenance. Its centrality measures (Callon Centrality 5.4984, Rank Centrality 2) indicate its importance as a leading application domain for AI within industrial environments. Scheduling algorithms represent another major thematic pillar, with a frequency of 1,453 keywords and similarly high centrality (Callon Centrality 12.2394, Rank Centrality 3). Dominant terms such as resource allocation, cloud computing, task scheduling, and edge computing underscore its relevance in optimizing performance within distributed and cloud-based systems. A fourth and comparatively smaller cluster, fabrication, includes only 22 keywords and features niche topics such as forming and papermaking. Its low centrality and density suggest that it represents an emerging or specialized area within the broader scope of AI-driven operations research.

Table 3. Research Themes with Centrality Metrics

Cluster	***Keyword Frequency***	***Centrality (Callon / Rank)***	***Key Associated Terms***	***Thematic Role***
Reinforcement Learning	*1,343*	*12.5388 / 4*	*Deep reinforcement learning, machine learning, optimisations, decision making, artificial intelligence*	*Foundational methodological hub*
Smart Manufacturing	*501*	*5.4984 / 2*	*Industry 4.0, digital twin, flexible manufacturing systems, predictive maintenance*	*Major application domain*
Scheduling Algorithms	*1,453*	*12.2394 / 3*	*Resource allocation, cloud computing, task scheduling, edge computing*	*Core thematic area addressing optimization*

Cluster	***Keyword Frequency***	***Centrality (Callon / Rank)***	***Key Associated Terms***	***Thematic Role***
Fabrication	*22*	*Low density and centrality*	*Forming, papermaking*	*Emerging/niche research area*

The interconnections across the three dominant clusters reveal not mere coexistence but a synergistic research ecosystem. Reinforcement learning functions as a core methodology that enables more advanced scheduling algorithms, which in turn support the optimization requirements of smart manufacturing systems. This alignment illustrates a systematic pipeline from algorithmic innovation to applies industrial deployment.

Word Cloud Analysis

A word cloud visualization was generated to provide a complementary overview of high-frequency terms within the dataset. The most prominent keywords such as *reinforcement learning*, *scheduling algorithms*, *smart manufacturing*, *cloud computing*, and *optimization* correspond closely with the dominant thematic clusters identified through keyword co-occurrence analysis. The visibility of additional terms such as *digital twin*, *resource allocation*, *industry 4.0*, and *edge computing* further illustrates the strong alignment between AI methodologies and their industrial and computational applications. While less structurally detailed than network-based approaches, the word cloud offers an accessible depiction of topic salience and reinforces the centrality of AI-driven operational innovation within the analyzed literature.

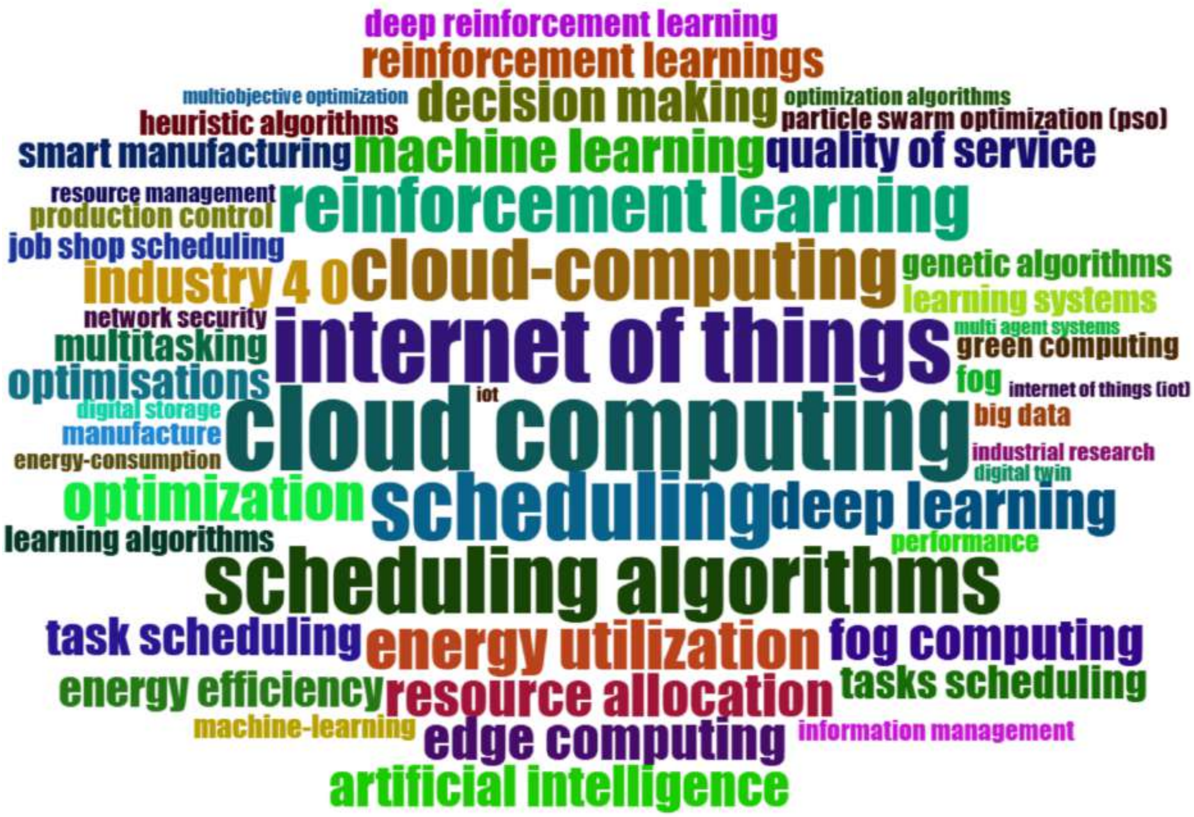

Figure 1. WordCloud

Temporal Evolution of Themes

Temporal analysis confirms that research within this domain is highly contemporary and rapidly expanding. For terms such as “reinforcement learning,” “reinforcement learnings,” and “scheduling algorithms,” the first quartile (Q1), median, and third quartile (Q3) publication years are all recorded as 2025. This compression reflects an inflection point in scholarly activity and suggests a globally competitive surge in research output, likely driven by industrial demand, increased funding, and rapidly maturing technologies.

Table 4. Trend Topics and their Quartile Years

Topic	Frequency	Year (Q1)	Year (Median)	Year (Q3)
Reinforcement learning	77	2025	2025	2025
Reinforcement learnings	77	2025	2025	2025
Scheduling algorithms	74	2025	2025	2025

Citation Dynamics and Early Impact

Given the recency of the dataset, traditional citation metrics such as total citations (TC), total citations per year (TC/Y), and normalized total citations (NTC) remain low or zero across most publications. As a result, network-based indicators—particularly PageRank and Normalized Local Citation Score (NLCS)—serve as more valid early markers of influence.

Documents such as "WANG X, 2025, IEEE Trans Autom Sci Eng" (PageRank 0.17738) and "ANAND J, 2025, Results in Engineering" (PageRank 0.16474) demonstrate strong structural relevance within the nascent citation network. Additionally, documents like "YU X, 2025, Alexandria Engineering Journal" exhibit high Normalized Local Citation Scores, signaling early influence within thematic clusters.

Despite low aggregate citation counts, some publications have already accrued notable citations, such as "NGUYEN HP, 2025, Energy Sources Recovery Util Environ Eff" (38 citations) and "GILL SS, 2025, Cluster Computing" (23 citations). These cases suggest early visibility and rapid dissemination in high-interest areas.

Table 5. Impactful Documents (by PageRank)

Author (Year)	Title	Source	PageRank
WANG X (2025)	Hybrid Task Scheduling in Cloud	IEEE Trans Autom Sci Eng	0.177
ANAND J (2025)	Efficiency-Aware Adaptive RL	Results in Engineering	0.165
HU Y (2025)	Green Optimization for Micro Data Centers	Applied Energy	0.149
YOUNESI A (2025)	Multi-Objective Scheduling in IoT	IEEE Trans Sust Comput	0.128
CUONG TN (2025)	Quantum Optimization in Terminals	Eng Appl Artif Intell	0.121

Discussion

The findings of this bibliometric analysis indicate a rapidly evolving yet nascent research domain centered on the application of Artificial Intelligence (AI) to operational systems. The temporal concentration of publications in 2025 and 2026 suggests the emergence of a hyper-accelerated research front rather than the gradual progression typical of mature fields. This accelerated growth aligns with broader global developments in automation, digital transformation, and Industry 4.0 (Dave, 2023; Sundaramurthy et al., 2022). The increasing integration of AI into logistics, manufacturing, and decision-making systems reflects the field's rapid transition from conceptual exploration to applied innovation (Soori et al., 2023).

A defining characteristic of this emerging landscape is the strong geographical concentration of research output in China. The dominance of Chinese universities and research institutions such as South China University of Technology, Islamic Azad University, and Beihang University indicates coordinated national investment and strategic prioritization of AI-driven operational technologies (Liu et al., 2020). This concentration not only highlights regional leadership in research but also reflects broader geopolitical and economic interests in securing global competitiveness in AI and Industry 4.0 domains (Xu et al., 2018).

The thematic structure of the field further underscores a tightly interconnected research ecosystem. Reinforcement learning (RL) has emerged as a core methodological driver, underpinning advances in scheduling algorithms and optimization processes (Pan et al., 2021; Wang et al., 2022). The prominence of RL reflects its ability to address complex, adaptive decision-making challenges, particularly in dynamic industrial and computational environments (Ekundayo, 2024). Smart manufacturing, another central cluster, represents the primary domain where these techniques are being operationalized, supported by the integration of cyber-physical systems, IoT infrastructures, and predictive maintenance technologies (Dave, 2023; Gao et al., 2022). The co-evolution of RL, scheduling algorithms, and smart manufacturing indicates a coherent research pipeline in which algorithmic innovation fuels advancements in industrial automation and operational efficiency.

The emergence of a smaller "fabrication" cluster suggests the early development of niche applications within the broader ecosystem, potentially representing new directions in materials processing, production technologies, or specialized manufacturing (De Sousa Jabbour et al., 2018). As with other emerging research fronts, such areas may gain conceptual and structural importance over time.

Temporal analysis reinforces this interpretation. The observation that the first quartile, median, and third quartile publication years for core topics all fall in 2025 suggests a synchronized surge in scholarly attention. Such temporal compression is atypical and reflects accelerating investment, perceived technological maturity, and industry demand (Donthu et al., 2021; Ekundayo, 2024). This trend indicates not just academic interest but also the likelihood of near-term application and commercialization.

Given the recency of publications in the dataset, traditional impact indicators such as total citations are not yet reliable. In this context, network-based metrics such as PageRank and Normalized Local Citation Score provide more meaningful measures of early influence, as they capture structural significance within the citation network before citation counts accumulate (Yan & Ding, 2009; van Eck & Waltman, 2014). The early citation activity observed in select 2025 publications further affirm rapid knowledge dissemination in high-visibility subfields.

The results also suggest promising directions for future research. Thematic convergence across AI methodologies, smart manufacturing, and cloud-based optimization points to opportunities for interdisciplinary advancement (Kumar, 2022; N et al., 2024). Potential areas of exploration include energy-efficient reinforcement learning models for edge and cloud computing, human-AI collaboration in manufacturing systems, and ethical governance in autonomous decision-making (Floridi et al., 2018). Additionally, the growing emphasis on digital twins, sustainability, and predictive analytics signals alignment with global industrial and environmental priorities (Gao et al., 2022; Zhang et al., 2019).

From a strategic and policy perspective, the findings carry important implications for academia, industry, and government stakeholders. The concentration of research leadership in China underscores the need for other regions to strengthen international collaboration, research capacity, and innovation ecosystems (Skute et al., 2017; Zucolotto et al., 2022). Investment in AI pilot projects, workforce development, and interdisciplinary partnerships will be critical for translating emerging research into industrial practice and competitive advantage (Dhillon et al., 2013).

Overall, the analysis affirms that AI-driven operations research is undergoing rapid expansion, characterized by thematic convergence, methodological innovation, and strategic regional dominance. The synergy among reinforcement learning, scheduling algorithms, and smart manufacturing reflects a transition from foundational research to applied impact, signaling the maturation of AI as a transformative force in operational systems.

Conclusion

The bibliometric analysis demonstrates that AI-driven operations research is advancing at an accelerated pace, with publications concentrated in 2025–2026, indicating an emergent and rapidly evolving research front. China's dominance in author productivity and institutional output reflects a strategic national focus on leveraging AI for industrial automation, smart manufacturing, and operational optimization. The field is thematically anchored in the synergistic interplay of reinforcement learning, scheduling algorithms, and smart manufacturing, forming a coherent innovation pipeline that links methodological development with applied implementation. Although traditional citation metrics remain limited due to the recency of publications, network-based indicators such as PageRank and Normalized Local Citation Score provide meaningful early measures of impact. The findings highlight opportunities for interdisciplinary research, including scalable AI models for complex scheduling, integration with cloud and edge infrastructures, and the incorporation of sustainability and ethical considerations. Overall, AI-driven operations research is transitioning from conceptual exploration to applied transformation, necessitating ongoing monitoring of research trends, collaboration dynamics, and thematic evolution to guide future advancements in the field.

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