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Review Article

Artificial Intelligence for Lean Systems: Systematic Review, Antecedents, Conceptual Mapping, and Future Opportunities

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Abstract

Lean systems thrive on eliminating waste by minimizing all non-value-adding activities. Therefore, significant technological developments such as artificial intelligence (AI) are expected to be swiftly adopted to elevate their performance. While several recent studies have investigated the integration of generic Industry 4.0 tools into lean systems, there is no comprehensive study of the integration of AI in lean systems. Therefore, this study investigates the evolution of the research integrating AI into lean systems from 1993 to 2024 using a thorough bibliometric analysis of 186 peer-reviewed articles retrieved from the Scopus and Web of Science databases. In addition to identifying the body of research's prevalent intellectual and social structures, thematic clusters and thematic maps are constructed to describe the relevance and development of various research themes. The results reveal no comprehensive and integrative framework with unified terminology and distinct research clusters. Furthermore, the findings indicate a concentration of the research contributions in a small set of developed countries, necessitating the deliberate channeling of funds to enhance this research focus in less developed countries. This work is the first study that explicitly tracks the integration of AI in lean systems and creates a convergent realm of analysis and application by identifying the key research foci and corresponding future trends.

Keywords:

Artificial Intelligence;

Lean Systems;

Review; Bibliometric;

Knowledge Domain.

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1- Introduction

Artificial intelligence (AI) is quickly spreading across all aspects of life in general and business in particular. The impact of AI on organizational performance, quality, and operations has proven to be swift and unparalleled [1]. From data collection to model construction and interpretation of findings, AI promises to provide unprecedented support for decision-makers [2] and to significantly impact process optimization [3]. AI can be defined as the ability of machines to mimic human intellectual processes through the exchange and exploitation of information [2]. As such, AI transcends machine learning to incorporate multiple facets of intelligence, such as perception and reasoning. The ability of "intelligent" machines to learn from data and identify optimal courses of action in economics and management without human intervention was argued by Herbert Simon as early as the mid-1960s [4], which made the application of AI to lean systems a logical and natural progression.

Lean thinking originated in Japan as an alternative management paradigm focusing on minimizing and eliminating waste and including all employees in continuously improving all organizational processes [5]. Any non-value-adding activity in a process is considered waste. Continuous improvement is a management philosophy and corresponding set of tools that advocates the gradual improvement of processes. Many "lean" concepts emerged to address various value chain components, such as lean manufacturing, lean production, and lean management. With little or no waste,

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organizations become agile and better positioned to react effectively to the changes in the dynamic environment in which they operate [6]. Identifying waste at the macro- and micro-levels requires thoroughly mapping the value stream [7]. Leanness assessment concepts and systems have been developed to gauge leanness gains, identify improvement areas [8], and devise customized lean management systems [9].

"Lean" and AI concepts have been introduced and researched independently for over three decades. However, and more recently, the integration of AI in lean systems has evolved as a new research endeavor. Despite the publication of several literature reviews and bibliometric analyses of lean or AI, review studies integrating AI and lean systems are quite scarce, with the majority focusing lopsidedly on one side of this interaction. Thus, it is apparent that, to the best of the authors' knowledge, there are no reviews or bibliometric analyses that look at the integration of AI in lean systems. This fact provides the necessary motivation for this work and clearly demonstrates its uniqueness. In this study, we aim to fill this gap by portraying the historical evolution of literature, uncovering fundamental structures of authors' and sources' networks, and classifying the main themes, trends, and likely future directions in the field.

The current study will, therefore, complement the broader reviews of Industry 4.0 or lean systems by investigating the specific applications of AI to lean systems. The objective is to provide practitioners with a bird's-eye view of the field to help frame and guide their concerns while providing academics with an appreciation of the field's stands and helping determine research themes and trends that are more relevant or pressing in the future.

The research questions pursued in this analysis are the following:

RQ1: What is the field's current status, and what dynamics best represent it?

RQ2: Which authors, journals, and articles are the most impactful?

RQ3: What intellectual and social structures are manifested through the analysis of the co-citation and collaboration networks?

RQ4: What are the prevalent conceptual structures in this research area?

RQ5: What are the key components of the field's thematic map, and what are the most promising venues for future research?

2- Literature Review

2-1- Triggers and Inhibitors of AI and Lean

A systematic review of AI for Industry 4.0 highlighting the key challenges and opportunities revealed that despite the uniformity of the problems faced, different industries pursued different adoption strategies [2]. This may be due to the various triggers and inhibitors prevalent in different industries. For instance, within the supply chain management (SCM) domain, triggers include environmental, social, and governance factors such as product waste and safety, product security, and quality and cost reduction. On the other hand, inhibitors encompass, among other things, data security and lack of regulation [10]. For instance, the storage space allocation problem, a significant inhibitor in SCM, can be addressed more effectively using AI-supported Decision Support Systems (DSS) [11]. In the healthcare sector, such systems become imperative to balance the efficiency requirements of hospitals with the life-saving needs of patients [12]. Furthermore, supply chains that use information technology tools such as mobile apps without leveraging the power of AI techniques risk seeing their resilience and sustainability degraded [13]. Alternatively, and despite the complexity of the logistics of manufacturing systems [14], AI technologies can significantly enhance the responsiveness of logistical networks [15].

2-2- Integration of AI and Lean

The relevance of AI to Economics in general and lean production in particular has been argued since the late 1990s [16]. AI-enabled processes and decision support systems can have a significant positive impact on key performance measures such as improved production sustainability, quality, equipment reliability, and cost structure. The application of Deep learning and the Internet of Things, among other AI tools, leads to better information flow and heightened levels of transparency and traceability of business processes [17, 18]. Applying these novel AI techniques can undoubtedly assist and enable a successful transition towards lean production [19] and boost manufacturing capabilities by strengthening quality improvement approaches [20].

Lean Six Sigma (LSS) is a quality improvement paradigm that has been shown to impact quality performance, customer satisfaction, and overall business excellence [21]. Integrating LSS with Industry 4.0 and quality management systems gives organizations a clear competitive advantage [22]. In the context of LSS in manufacturing, AI and other Industry 4.0 technologies have contributed to achieving operational excellence [23] and heightened product quality and competitiveness [24]. In fact, quality experts perceive AI to be among the critical success factors for any LSS system [25]. For high-development-cost industries such as the pharmaceutical industry, combining AI techniques with LSS could substantially improve research productivity [26]. Integrating AI techniques and green LSS proved instrumental in mitigating the effects of global crises such as the COVID-19 pandemic [27]. However, to deliver the anticipated organizational and operational improvements, integrating AI and LSS requires the full support of senior management [28] and proper project portfolio selection [29].

Manufacturing processes were optimized using machine learning and the reinforcement of learning algorithms for textile draping in composite manufacturing [30]. Recall that lean philosophy centers on waste reduction and optimizing manufacturing lines and assembly systems [31]. AI-based techniques were used to minimize machine downtime, a common form of waste, by predicting potential system failures to prevent future interruptions [32]. Efficiency gains through reducing idle time have also been reported as the outcome of integrating collaborative robotics and AI with lean manufacturing [33]. When it comes to reducing rework waste, AI-powered image classification algorithms outperformed the human eye in identifying defects and preventing them from moving further in the value chain [34]. Computer vision using AI has achieved zero defects, reducing production time and workforce size [35]. Similarly, an automated inspection system can improve productivity and enhance product quality [36]. Decision support systems that can accurately prioritize critical defects directly affect recovery rates and rework costs [37]. Furthermore, DSS with appropriate AI tools provides sustainability in shop floor management systems with significant operational constraints [38] and enhances operational excellence [39].

Reducing waste improves productivity since fewer inputs are used in output generation. Hence, sustainable production planning models encompassing AI tools enhance productivity levels, particularly when resources are restricted [40], and reduce energy consumption without compromising quality [41]. This productivity improvement is also manifested by the increased operational activity of applying AI tools to work systems in global value chains [42]. For SMEs, enabling lean-green practices through digitization and AI-powered techniques improves performance measurement systems and value chain integration [43]. Notwithstanding its intermittent project nature, lean construction management, which is argued to be a form of temporary production system, has benefited significantly from AI tools in bolstering its activities [44]. Indeed, applying AI tools, such as twin information systems [45], to lean construction has been reported to improve time and cost predictability [46] and impact the effectiveness and efficiency of operations as well as long-term sustainability [47].

In materials procurement and order fulfillment, AI-based office automation tools were developed to reduce lead time, improve material and manufacturing requirements planning [48], and achieve desired customer service levels [49]. The accurate prediction of the outcome of an operational variable and the selection of a corresponding course of action improve efficiency. In a high fixed-cost industry such as oil and gas, improving the selection of wells for workovers decreased selection time by over 90% and increased the success rate by almost 20% [50]. AI-inspired techniques were shown to improve energy efficiency in many cases by anywhere from 15% to 25% globally [51]. On a broader scale, AI-driven knowledge management systems play a central role in mitigating inherent uncertainty and complexity, thus enabling leaner and more agile supply chains [52].

Lean startups are concerned with generating innovative ideas within shortened development cycles [53]. Harnessing the power of AI in lean startups leads to improved prediction of the desirability of product design decisions [54]. Naturally, these decisions influence the overall customer experience, which can be significantly enhanced by AI and lean management techniques in a holistic lean customer experience management framework [55].

2-3- AI and Lean Reviews

Literature reviews and bibliometric analyses integrating AI and lean systems are limited. One such study investigated sustainable industrial and operations engineering in the Industry 4.0 context using bibliometric tools complemented with the fuzzy Delphi analysis method [56]. The study was confined to works indexed in the Scopus database till December 2020 and included 436 publications. Eight distinguishable clusters were identified, including lean manufacturing in Industry 4.0 and AI for sustainability. Another study reviewed high-tech applications for production systems and highlighted the benefits of an integrated cyber-physical production system [57]. The study reviewed a few salient publications on the topic without using bibliometric techniques. The authors identified two promising future research patterns: the management of real-time information and the decentralization of decision-making. As was mentioned, the integration of the broader Industry 4.0 with lean concepts in the literature is still very recent and limited. An early attempt at developing a conceptual understanding of lean tools and their linkage to Industry 4.0 was presented in Shahin et al. [58], with a further elaboration in Javaid et al. [59]. Shahin et al. [58] carried out a structured literature review of what they deem as a comprehensive list of articles on the integration of lean practices and Industry 4.0. There is no mention of the selection criteria or the databases used, limiting the work's replicability. Nonetheless, the findings confirmed the potential gains while warning of the tendency to implement technology uniformly to products, services, and processes, as they found evidence of a difference in their moderation effects on lean practices. Javaid et al. [59], on the other hand, carried out a structured literature review on articles extracted from Scopus, WoS, ScienceDirect, and Google Scholar. While there is no mention of the retention criteria, the authors concluded that Lean 4.0 would boost companies' value propositions and significantly impact career paths. Similarly, a review article spanning the 2010-2022 period investigated the mutual effect of lean on Industry 4.0 and vice versa [60]. From the Scopus database, the authors identified 661 articles related to lean and Industry 4.0 and 146 to lean and digital transformation. Through a bibliometric analysis, the absence of any meaningful theoretical integrative framework was ascertained. A systematic literature review of the application of AI to LARG (lean, agile, resilient, green) manufacturing highlighted the significant operational, economic, and environmental benefits of the resulting synergy [61]. Spanning the 1990-2018 period, articles, books, and conference papers related to LARG manufacturing were identified from publishers' databases such as Elsevier and Emerald Insight. No bibliometric tools were used to complement the review.

2-4- Literature Gap Analysis

Although some of the above-mentioned studies discussed the relevance of AI to lean, they fall short of presenting a comprehensive bibliometric analysis of AI's integration into lean systems or outlining the field's current thematic and conceptual structure. Several studies have investigated the integration of Industry 4.0 tools and technologies into generic lean systems [5, 58-61]. However, when we consider the topical scope of lean systems relative to the technology scope, we observe that the study of AI has only been considered in the context of subtopics of lean systems such as lean manufacturing [16] and lean construction [44]. Therefore, the integration of AI into the comprehensive lean system has not been investigated and thus represents a research gap that we are filling with this study. Table 1 summarizes the related literature reviews regarding topical and technological scopes and highlights the key gaps in literature.

Table 1. Gaps in AI-Lean Reviews

		Technology Scope			
		Industry 4.0	AI	CPS	IOT
Topical Scope	Lean Systems (Comprehensive)	Alsadi et al. (2023) [60] Singh & Singh (2023) [5] Javaid et al. (2022) [59] Amjad et al. (2020) [61] Shahin et al. (2020) [58]	GAP*	GAP	GAP
	Lean Manufacturing	GAP	Prem (1997)	GAP	GAP
	Lean Supply Chain	Kaswan et al. (2024) [27]	GAP	GAP	GAP
	Lean Construction	GAP	Dumrak & Zarghami (2023) [44]	GAP	GAP
	Quality Management	Rifqi et al. (2021) [1]	GAP	GAP	GAP
	Lean CRM	Chatzopoulos & Weber (2021) [55]	GAP	GAP	GAP
	Process Optimization	GAP	GAP	Rossit et al. [57] (2019)	Mateo & Redchuk (2022) [3]

*Note: * indicates the positioning of our work relative to existing reviews.*

3- Research Methodology

Aria & Cuccurullo [62] argued that the systematic nature of bibliometric analysis ensures findings' replicability, objectivity, and reliability. As such, we used bibliometric analysis to explore the AI and Lean literature, identify trends in research themes, and address the research questions. To conduct this research, we followed the framework proposed by Donthu et al. [63], which includes the following four steps: 1) Defining the aims and scope of the bibliometric study, 2) Choosing the techniques for bibliometric analysis, 3) Collecting the data for bibliometric analysis, and 4) Running the bibliometric analysis and reporting the findings.

3-1- Defining the Aim and Scope of the Bibliometric Study

This study aims to provide a comprehensive overview of AI and Lean literature using bibliometric analysis. By analyzing all publications indexed in Scopus and WOS, we aim to thoroughly analyze the research domain by exploring the current dynamics in the field and identifying its conceptual structure, trends, and hotspots based on the five research questions presented in the introduction.

3-2- Choosing the Techniques for Bibliometric Analysis

The selection of the analysis techniques depends mainly on the scope of the study. The current study uses performance analysis and science mapping as the primary data analysis techniques. We use performance analysis measures to examine the contributions of the different research constituents, including the most influential authors, institutions, countries, and journals. This descriptive analysis is a central feature of bibliometric studies [63]. Using science mapping, we examine the relationships between research constituents [64] and present the intellectual interactions and structural connections using citation and co-citation analyses, as well as co-word analysis. Combining the two techniques can provide a holistic view of the research domain.

3-3- Collecting the Data for Bibliometric Analysis

The Scopus and Web of Science (WoS) databases were selected for the analysis. Although the Scopus database has comprehensive and recent coverage [65], there is a consensus developing that using Scopus and WoS in conjunction ensures the broadest coverage of peer-reviewed journal articles and conference proceedings [66].

The following search query was used to identify potentially relevant articles:

(“artificial intelligence” ***OR*** *“AI”* ***OR*** *“artificial intelligence (AI)”* ***OR*** *“artificial intelligence-AI)”)* ***AND*** *“Lean”.*

The query was limited to peer-reviewed journal articles and conference proceedings written in English and generated 321 and 51 articles from the Scopus and WoS databases, respectively. A search refinement process was then carried out to filter the set by excluding articles that did not match the study’s objectives. The exhaustive list of keywords from the generated articles was inspected, and any works with keywords that did not relate to our research were removed. For example, keywords related to “lean” in the food, agriculture, and medical fields were not retained. The remaining articles were then evaluated individually by reading the abstract and determining whether the article fit the scope of the work. This elimination process yielded 155 articles from Scopus and 43 from WoS. Electronically merging and removing duplicates resulted in 10 articles being dropped. Last, we performed a manual inspection, which resulted in removing another two duplicates. Inconsistencies in the data (e.g., using abbreviated and full journal names, country names being presented differently, and affiliations not reported) were resolved by returning to the original documents. Figure 1 represents a graphical summary of our methodological approach.

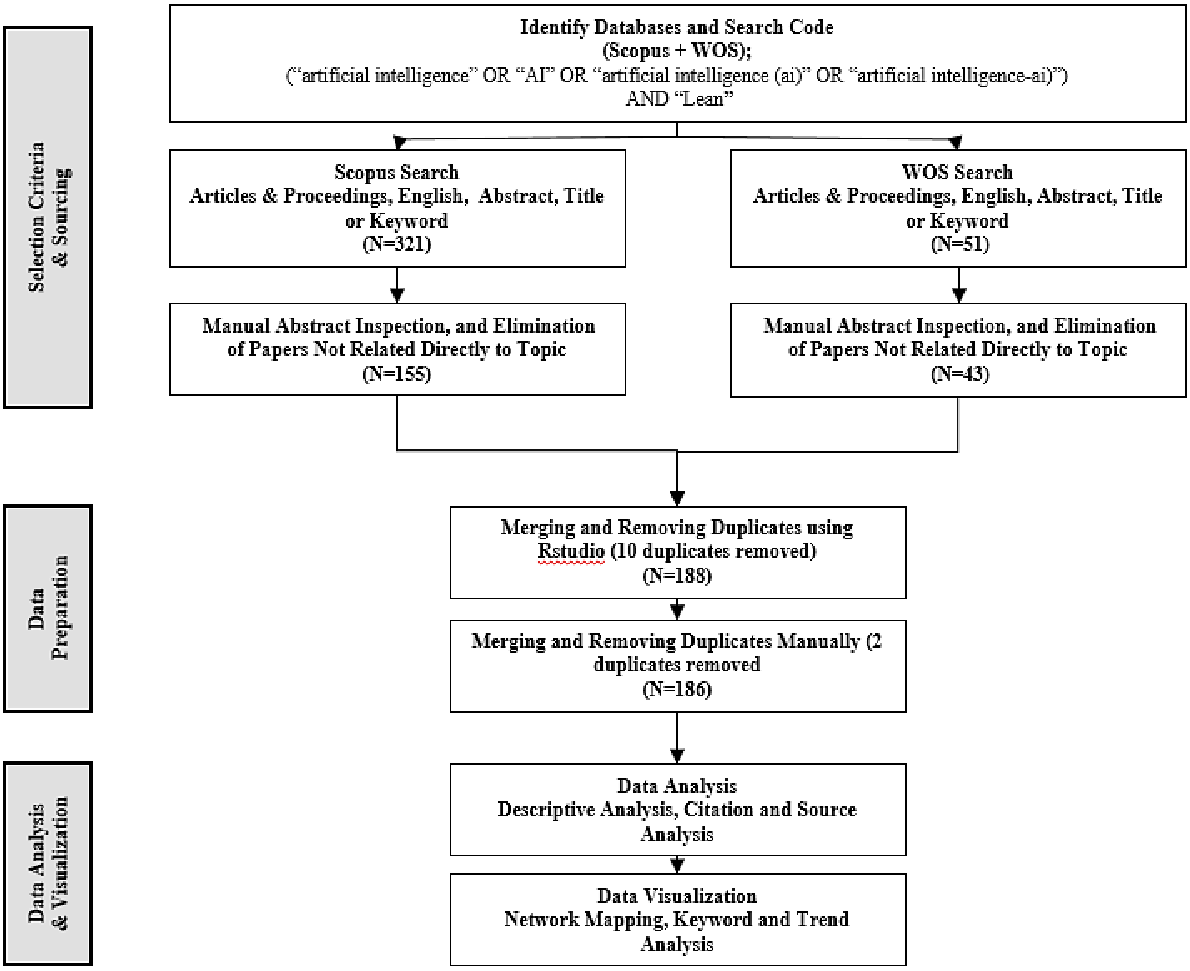

Figure 1. Methodological approach

3-4- Running the Bibliometric Analysis and Reporting the Findings

We used biblioshiny and VOSviewer to conduct the analysis. Biblioshiny is an RStudio library used to generate a particular dataset’s performance measures, including, but not limited to, the research status, most influential authors, and leading publication venues [63]. In parallel, VOSviewer was used to generate the different visualization maps, including the authors, institutions, and countries’ collaboration and co-citations maps [67]. This practice is common in bibliometric research, as both analyses often go hand in hand to generate bibliometric summaries and provide readers with a better understanding of the findings.

4- Analysis and Results

4-1- Data Summary

As detailed in Table 2, 186 articles from 139 sources spanning the 1993-2024 period were analyzed. The articles were written by 573 authors, with an average number of co-authors equal to 3.39. A striking observation is that only 15 manuscripts are single-authored, clearly marking the interdisciplinary and multidisciplinary nature of the field. Ironically, though, only 5.914% of the articles have international co-authorship, which means that collaborations are mostly intranational. Even though the average age of articles is 6.24 years, they enjoy a high average citation per article of 15.19, clearly showing the relevance and significance of this topic.

Table 2. General description of the data

Description	Results
Main Information About Data	
Timespan	1993:2024
Sources (Journals, Books, etc)	139
Documents	186
Annual Growth Rate %	8.63
Document Average Age	6.24
Average citations per doc	15.19
References	8106
Document Contents	
Keywords Plus (ID)	1248
Author's Keywords (DE)	665
Authors	
Authors	573
Authors of single-authored docs	15
Authors Collaboration	
Single-authored docs	15
Co-Authors per Doc	3.39
International co-authorships %	5.914
Document Types	
Article	88
Article; proceedings paper	3
Conference paper	60
Proceedings paper	24
Review	10
Review; early access	1

Regarding growth, research integrating AI and lean witnessed a significant average increase of over 8.63% per year. However, as shown in Figure 2, the number of publications experienced explosive growth starting with 2018, which continued strong till 2023. Developments in AI technologies and lean methodologies are a primary driver for this inflation in research interest. The dip in the number of articles in 2024 is an artifact of data collected in that year's first quarter.

4-2- Most Relevant Sources

Table 3 lists the 20 most relevant sources based on the number of articles. The journals leading the research in this field are the *International Journal of Production Research (10 publications), International Journal of Lean Six Sigma (4 publications), Total* Quality *Management (*now *Total Quality Management and Business Excellence) (4 publications), and Expert Systems with Applications (3 publications)*. Although they represent only 2.8% of the sources, these journals account for almost 12% of the scientific production on this topic. Noteworthy is the fact that these are all top-tier journals that are ranked as Q1 in Scopus. This is indicative of the importance of this stream of research to academic thought leaders and readership around the world.

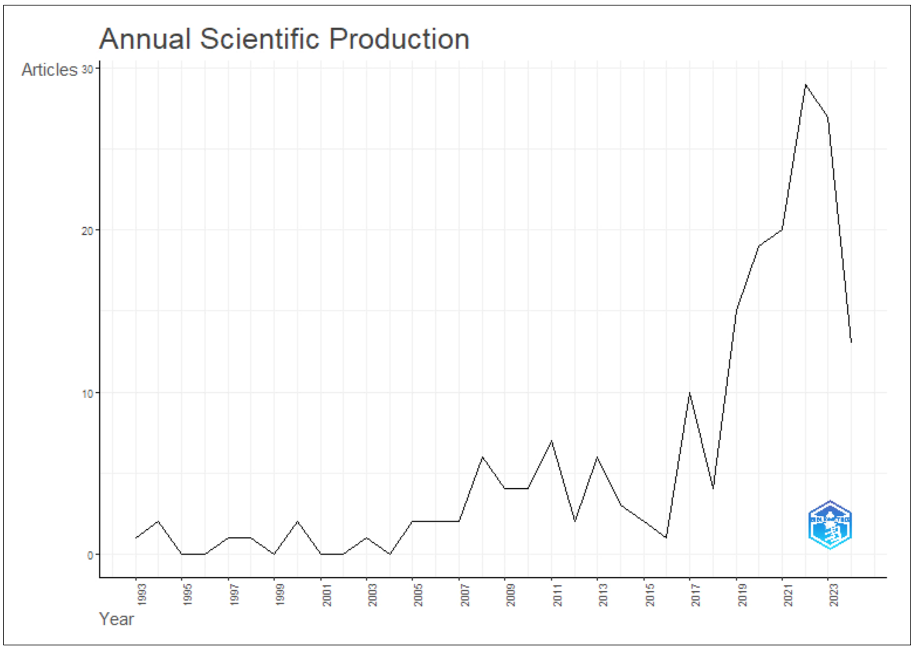

Figure 2. Annual scientific production (1990-2024) of peer-reviewed publications

Table 3. Most relevant Sources

Sources	Articles	2023 Scopus Rank
International Journal of Production Research	10	Q1
Advances in Production Management Systems: Artificial Intelligence for Sustainable and Resilient Production Systems, APMS 2021	5	
International Journal of Lean Six Sigma	4	Q1
TQM Journal	4	Q1
2016 IEEE International Conference on Computational Intelligence and Computing Research, ICCIC 2016	3	
30th Annual Conference of the International Group for Lean Construction, IGLC 2022	3	
ACM International Conference Proceeding Series	3	
Expert Systems with Applications	3	Q1
Procedia CIRP	3	
Proceedings of the International Conference on Industrial Engineering and Operations Management	3	
2022 2nd International Conference on Electrical Engineering and Control Science, IC2ECS 2022	2	
27th Annual Conference of the International Group for Lean Construction, IGLC 2019	2	
Advances in Transdisciplinary Engineering	2	
Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	2	
Engineering, Construction and Architectural Management	2	Q1
International Journal of Online and Biomedical Engineering	2	Q2
Journal of Quality in Maintenance Engineering	2	Q2
Journal of Theoretical and Applied Information Technology	2	Q4
Management and Production Engineering Review	2	Q3
Mathematical Problems in Engineering	2	Q2

A complementary way of gauging the impact of sources is using Bradford's law, presented in Figure 3. According to Bradford's law, sources are clustered into three categories. The first category includes the most productive sources in the discipline, whereas the second and third categories contain the moderate and low publication venues [68]. The core category of outlets for research on AI in lean systems includes the *International Journal of Production Research*, *International Journal of Lean Six Sigma*, *Total Quality Management, and Expert Systems with Applications*, validating the results presented in Table 3. Of particular interest is the presence of several conference proceedings in the core category, which can be explained by the relevance of the topic and the fact that research in the area is booming, with new ideas being typically first introduced at conferences.

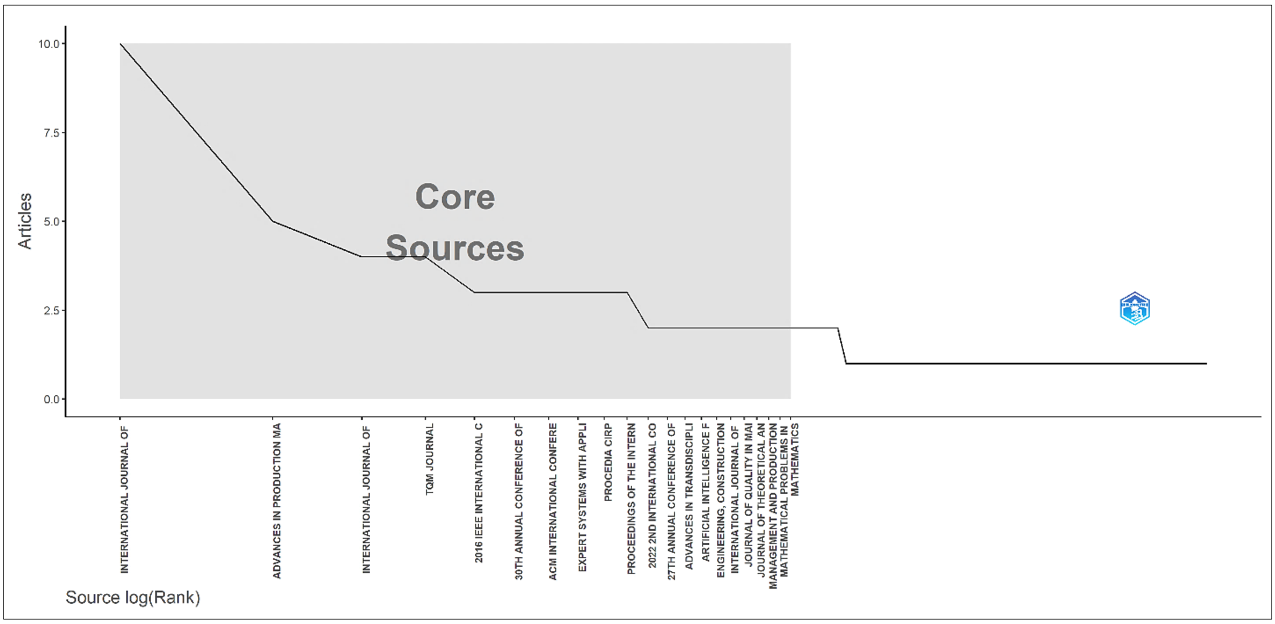

Figure 3. **AI in lean systems scholarly research graphically represented according to Bradford's law**

4-3-Most Globally Cited Articles

Seminal works that shape the discipline by tapping into undiscovered areas, laying its theoretical foundations, or modeling paradigms are normally cited the most. Coito et al. [69], "Lean automation enabled by Industry 4.0 technologies," topped the list with the most citations (866 in Google Scholar and 464 in Scopus), with a significant lead over the closest article by Sacks et al. [45] on "Construction with digital twin information systems," with 370 Google Scholar citations (218 Scopus). The significance of the top-cited article stems from its establishment of a theoretical background for integrating Industry 4.0 and Lean, making the case for its timeliness and importance, and arguing for the necessity of a comprehensive framework. Table 4 presents key citation statistics of the top 20 cited articles linking AI to lean systems, whereas Table 5 provides a brief overview of each article's purpose, methodology, findings, and industry.

Table 4. **Most cited articles**

Paper	Reference #	Total Citations	TC per Year	Normalized TC
KOLBERG D, 2015, IFAC PAPERSONLINE	[69]	318	31.8	2
SACKS R, 2020, DATA-CENTRIC ENG	[45]	218	43.6	7.4765343
TSENG ML, 2021, J IND PROD ENG	[56]	177	44.25	11.8791946
HU G, 2008, INT J PROD RES	[29]	129	7.58823529	2.83516484
SHAHIN M, 2020, INT J ADV MANUF TECHNOL	[58]	117	23.4	4.01263538
VINODH S, 2012, INT J PROD RES	[8]	116	8.28571429	3.60888889
JAIN V, 2008, INT J PROD RES	[70]	82	4.82352941	1.8021978
LEE CKM, 2011, EXPERT SYS APPL	[71]	78	5.57142857	2.42666667
LIU S, 2013, INT J PROD RES	[52]	72	6	3.32307692
ROSSIT DA, 2019, INT J COMPUTER INTEGR MANUF	[57]	72	12	6.03351955
HWANG R, 2009, INT J PROD RES	[72]	71	4.4375	2.21875
YADAV N, 2020, TQM J	[22]	66	13.2	2.26353791
LOPEZ-PEREZ D, 2022, IEEE COMMUN SURV TUTOR	[73]	59	19.6666667	8.10900474
LI L, 2009, INT J PROD RES	[74]	55	3.4375	1.71875
YADAV N, 2021, INT J QUAL SERV SCI	[25]	52	13	3.48993289
JAN Z, 2023, EXPERT SYS APPL	[2]	48	24	12.7058824
VINODH S, 2008, INT J PROD RES	[75]	43	2.52941176	0.94505495
PULLAN TT, 2013, PROD PLANN CONTROL	[76]	43	3.58333333	1.98461538
NABELSI V, 2017, INT J PROD RES	[12]	41	5.125	3.8317757
KOULOURIOTIS DE, 2010, INT J PROD RES	[31]	37	2.46666667	2.27692308

Table 5. **Top 20 cited articles**

Article	Total Citations	Purpose	Methods	Main findings	Industry/ Sector
[69]	318	Provide an overview of existing applications combining lean production and automation technology.	Position paper, theoretical reasoning	The integration of innovative automation technology in lean production is a promising and timely topic. There is no comprehensive framework for combining Industry 4.0 and Lean production.	Generic
[45]	218	Develop a mode of construction that uses digital twin information systems to achieve closed-loop control systems.	A DTC (digital twin construction) information system workflow comprising information stores, information processing functions, and monitoring technologies is developed according to three concentric control workflow cycles.	Instead of considering it as a simple extension of BIM (Building Information Modeling), a DTC should be viewed as a comprehensive mode of construction that prioritizes closing the control loops.	Construction
[56]	177	Analyze contemporary sustainable industrial and operations engineering within an Industry 4.0 context.	Bibliometric review and the fuzzy Delphi method	30 indicators are identified and clustered into eight study groups: 1. Lean manufacturing in Industry 4.0, 2. Cyber-physical production system, 3. Big data-driven and smart communications, 4. safety and security, 5. Artificial intelligence for sustainability, 6. The circular economy in a digital environment, 7. Business intelligence and virtual reality, 8. Environmental sustainability	Generic
[29]	129	Develop a unique decision support system for the project portfolio selection problem in manufacturing companies.	Multi-objective programming	The proposed model can be used to implement Lean and Six Sigma concepts effectively.	Semi-conductors manufacturing
[58]	117	Provide a comprehensive review and report on links between Lean tools and Industry 4.0 technologies.	Comprehensive review	The simultaneous implementation of Lean tools and Industry 4.0 technologies has a positive effect on the operational performance of factories.	Generic
[8]	116	Develop a decision support system (DSS) for the multi-grade fuzzy leanness assessment (MGFLA) (DSS-MGFLA) problem.	The Fuzzy method was used for leanness assessment, and a DSS- MGFLA was developed.	The proposed DSS- MGFLA accurately evaluates leanness and enables the identification of areas for improvement.	Relays manufacturer – India
[70]	82	Develop a novel approach to model agility and introduce the dynamic agility level index (da_{li}) using fuzzy intelligent agents.	Fuzzy intelligent agent-based framework	The proposed approach is capable of providing supply chain decision-makers and practitioners with relatively realistic and informative insights.	Illustrative example
[71]	78	Examine how AI and RFID can enhance the responsiveness of the logistical workflow.	Artificial Neural Networks and the formulation of a structural framework of responsive logistics workflow system (RLWS).	The RLWS improves efficiency via faster and better data flow and provides correct replenishment strategies due to better identification of demand patterns.	Jewellery group
[52]	72	Develop a decision-focused knowledge management framework to support collaborative decision-making for lean supply chain management.	Using artificial intelligence system shells visirule and Flex	The developed framework is shown to provide efficient and effective support for collaborative decision-making in supply chain waste elimination.	Dell laptop global supply network
[57]	72	Review the most salient research on scheduling in Cyber-Physical Systems (CPS).	Structured literature review and analysis	The availability of information in real-time will have a significant impact on CPS scheduling. Additionally, it will be possible to solve scheduling in decentralized decision processes in the future.	Generic
[72]	71	Propose a new evolutionary approach to handle workload balancing problems in mixed-model U-shaped lines.	A method based on the multi-decision of an amelioration structure to improve variations of the workload	The results of the experiments showed an improvement in the decision-making process during multi-model, assembly line, and system production.	Boiler-producing industry in Japan
[22]	66	Compare the impact of Industry 4.0 and emerging information with communication technologies.	Survey of 105 Indian organisations	There is a statistically significant difference among 20 organizational performance indicators under different combinations of Industry 4.0 and communication technologies.	Various
[73]	59	Review the state-of-the-art research on current energy efficiency	Structured literature review	The necessity of adapting networks' resources to consumers' needs, the importance of machine learning in forecasting and optimization	Generic

[74]	55	Develop an approach to detect throughput bottlenecks in serial production lines and manufacturing systems with complex layouts.	Data-driven, simulation-based, heuristic	The formulated approach enables plant managers to quickly pinpoint the throughput-critical location to utilize finite manufacturing resources for throughput improvement efficiently.	Automotive assembly
[25]	52	Identify the critical success factors (CSF) for Lean Six Sigma (LSS) using quality 4.0.	Exploratory factor analysis	20 factors are evaluated for LSS success (7 factors related to quality 4.0 technologies and 13 related to conventional technologies)	Generic
[2]	48	Identify common themes and concerns related to the adoption of AI technologies in the context of Industry 4.0	Systematic review	Although different industries share common issues, the adopted solutions are often specific to a particular industry sector, which may be difficult to transfer to other sectors.	Generic
[75]	43	Trace the origin and development of agile manufacturing and assess the necessary activities to acquire agility.	A quantification model is developed.	A Decision Support System for quantifying Agile Criteria (DESSAC) was developed and tested.	Electronics switch manufacturer- India
[76]	43	Develop a Concurrent engineering framework for lean manufacturing	Application of information technology and object-oriented methodology	The proposed framework decreased product development lead-time by more than 50% compared to conventional development projects. Consequently, the need for rework was found to be negligible, and the development cost was reduced considerably.	Machine tool manufacturer, India
[12]	41	Investigate the effect of business process management and reengineering projects on the supply chains of two major urban hospitals.	Mixed research method: qualitative data and statistical analysis	SCM reengineering projects must take into account the specific IT application area (e.g., enterprise systems, networking, data centers, mobile solutions). Additionally, information and process architecture requires more automated testing to overcome constraints and implement truly customer-focused processes effectively	Hospital - Canada
[31]	37	Extend the application of the Base Stock, Kanban, CONWIP, CONWIP/ Kanban Hybrid, and Extended Kanban production control policies to assembly systems that produce final products of a single type.	Discrete-event simulation and genetic algorithm with resampling.	The Generalized and Extended Kanban mechanisms can outperform less-sophisticated mechanisms such as the Kanban and the Base Stock. The development of new and efficient AI-based production controllers is a challenging but promising research topic.	Manufacturing

4-4- Most Influential Authors

In addition to seminal articles, some researchers emerged as thought leaders who play a central role in defining the field. A common approach for identifying these leaders is through their research productivity. Table 6 presents the top 10 authors in terms of research productivity. Due to the recency of the discipline, there isn't a single author that is dominating the field. Alternatively there are five authors leading the pack with 4 articles each. A look at the research productivity over time provides further insight into when thought leaders generated most of their output. Figure 4 shows the authors' production over time. A striking remark here is that most productive authors started contributing to this field after 2020, with a sizeable portion of them after 2022, clearly indicating that the field is still in its infancy.

Table 6. Most productive authors

Authors	Articles	Articles Fractionalized
CHATTOPADHYAYA S	4	0.53
LI C	4	0.53
MUKHOPADHYAY AK	4	0.53
SHARMA S	4	0.53
TRIPATHI V	4	0.53
ANTONY J	3	0.49
BOUZARY H	3	0.7
SHAHIN M	3	0.7
CHEN FF	2	0.45
HOSSEINZADEH A	2	0.45

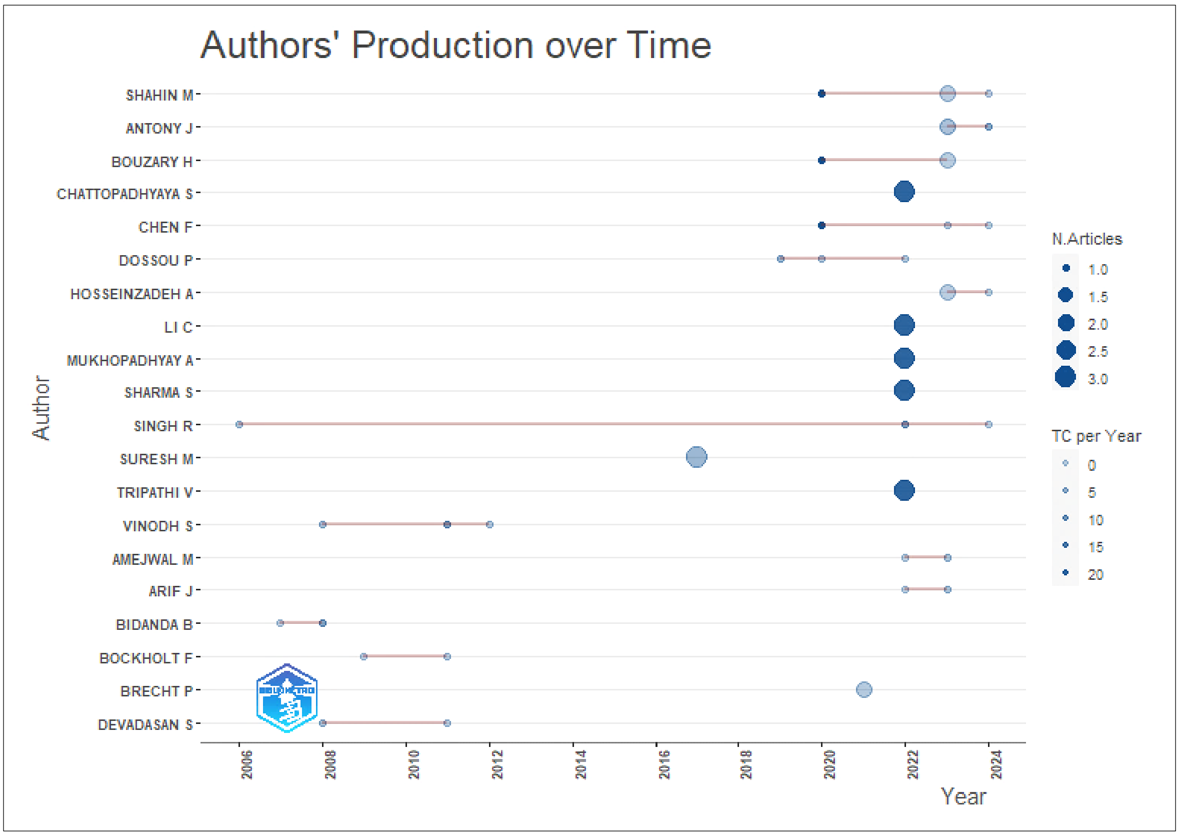

Figure 4. AI in lean systems author dominance over time

4-5- Authors Co-citation Network

Co-citation refers to the event where a third author concurrently cites two articles. Analyzing co-citation networks is a standard bibliometric tool used to comprehend the intellectual structure of a discipline. The network comprises nodes (bubbles in the figure) and dashes (or arcs), where the former corresponds to authors and the latter to co-citation linkages. Nodes with more arcs are represented by larger bubbles, which are more centrally located in the network and indicate more prominence in the research area. On the other hand, nodes with fewer connections are represented by smaller bubbles and tend to be positioned at the peripheries of the network. Additionally, the proximity of nodes indicates the degree of co-citation and emphasizes similar research themes. Arcs portray the presence, and their thickness indicates the strength of linkages. As such, denser arcs describe more occurrences of simultaneous citations for the connected authors. Nonetheless, the most important phenomenon observed is clustering, which groups authors most frequently co-cited together. Clusters identify nodes with thematic similarities, and some specific clusters can act as gateways between different network nodes performing the role of knowledge and information transfer facilitators.

By inspecting Figure 5, it becomes apparent that there are five distinct clusters. The Red cluster is the largest, with 15 authors. However, the cluster is located at the network's periphery with numerous sub-clusters. Sacks R. has the largest bubble in the cluster, which implies that the author is being co-cited frequently. However, the bubble is located at the edge of the network, indicating that most of the co-citations occur within a closely related field of research. On the other hand, Liu Y. occupies a smaller bubble that is more centrally located, which implies co-citations with authors from different research themes. The green cluster is the second largest and comprises 10 authors. It is also located at the edge of the network. Antony J. occupies the most prominent bubble and is centrally located relative to the sub-clusters. This shows that Antony's co-citations occur both within and outside the cluster, which signifies his broader interdisciplinary research themes. The peripheral positioning of these clusters indicates that those authors focus on thematically distinct ideas in their work. With the same number of authors as the green cluster, the blue cluster has 10 authors and is the most centrally located cluster in the network. Gunasekaran A. has the largest and the most centrally located node. This indicates a "bridging" cluster that links diverse research themes and acts as a medium for transferring findings across distinct research foci. The remaining two clusters are in yellow with four authors and in purple with two authors and are located at the periphery, with most of the co-citations occurring within the same cluster, which could indicate them being 'siloed' with the exception of Chen F. in the yellow cluster and Vinodh S. in the purple cluster, who occupy more central locations, indicating more interdisciplinary research themes.

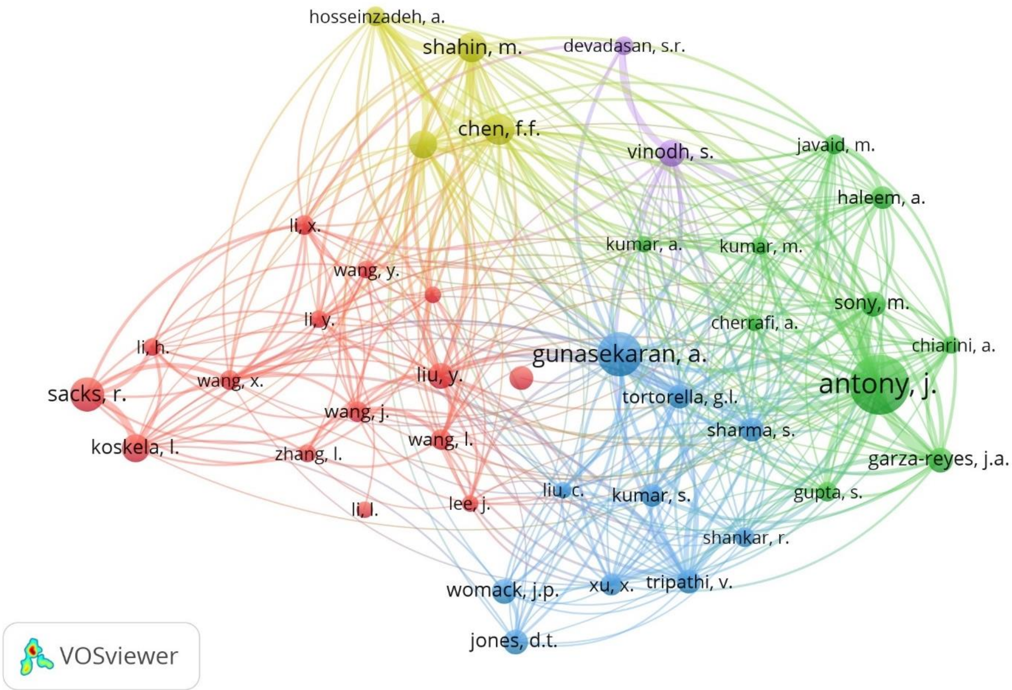

Figure 5. **AI in lean systems author co-citation network**

4-6- Sources Co-citation Networks

Similar to authors' co-citation networks, source co-citation networks investigate whether specific sources are more likely to be cited together, unveiling possible similarities in scope and research themes. This information is valuable for helping researchers identify journals with similar foci but may reach different audiences to expand the impact of their research. The map presented in Figure 6 reveals four clusters of journals of varying sizes. The Red cluster is the largest, with 12 journals, and is the most centrally located cluster. It comprises some of the top-ranked journals in the management arena. Among these, the *International Journal of Production Research* and the *International Journal of Production Economics* emerge as the pillars in this group, accounting for most of the citations. However, the *International Journal of Production Research* occupies a central location and serves as a bridge between research outlets in different clusters. This may be explained by its broader scope when compared to the *International Journal of Production Economics*. By looking at the scopes of the journals in this cluster, we observe themes that span the broad spectrum of production systems' issues, ranging from product and process design to strategy and policy formulation, which could explain why this cluster seems to be the most central. The green cluster is the second largest with five periodicals. Three of the five sources are located at the periphery, implying more limited scopes, such as *Sensors* and *International Journal of Advanced Manufacturing Technologies*, or multidisciplinary perspectives, such as *Sustainability*. The blue cluster is the third largest with four sources. *Automation in Construction* occupies a sizeable bubble at the edge of the network indicating its significance in the lean construction domain but little connection to other lean themes. The yellow cluster is also comprised of four journals. It is marginally located at the network's edge, indicating a limited scope and little interaction with other journals. The journals in this cluster focus more on the quality dimension and include *Total Quality Management* and the *International Journal of Lean Six Sigma*.

4-7- Authors Collaboration Network

Unlike the authors' co-citation networks, which describe the intellectual structure, collaboration networks depict the field's social structure by identifying clusters of researchers who publish together. Since collaborations do not always occur between researchers in the same institution or geographical region, significant information is generated regarding the underlying "invisible college" connecting the research field [67]. Figure 7 depicts our dataset's network. The immediate observation is that the collaboration clusters form three, relatively independent silos, indicating the limited nature of research collaboration among researchers in this field. The red cluster is the largest and consists of six authors. The collaboration is mainly within the cluster with moderate branching to other parts of the network, namely to authors Sony M. in the red cluster and Antony J. in the green cluster. By inspecting the articles and keywords associated with authors in this cluster, we observed that the authors are predominantly Indian and focus on integrating technology into manufacturing and quality control systems. The green cluster is the second largest and contains five authors. Although smaller in terms of the number of authors, it occupies a more central position and acts as a bridge between the different clusters. In particular, author Antony J. has the most prominent node and the highest number of connections to authors from within and outside the cluster. Considering the articles and keywords, we found the cluster focusing on review articles on integrating technology into various facets of lean systems. Lastly, the blue cluster consists of five authors and is focused on lean six sigma integration with Industry 4.0. Sony M. occupies a sizeable central node and has numerous links to authors from outside the cluster. This apparent independence of clusters may be explained by the recency of the field and the tendency of each cluster to focus on laying down the foundations for the discipline.

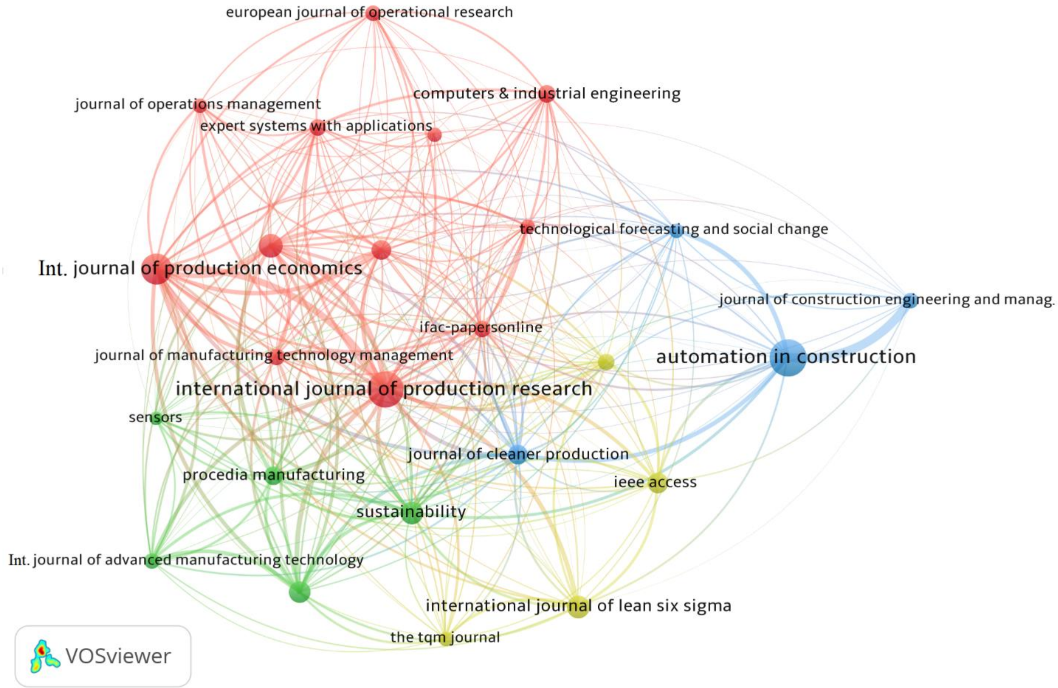

Figure 6. AI in lean systems source co-citation network

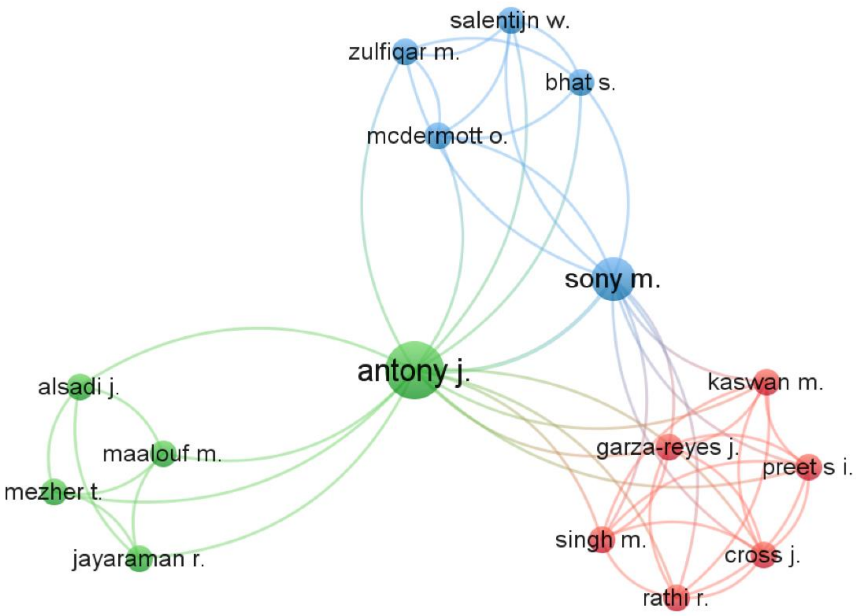

Figure 7. AI in lean systems author collaboration network

4-8- Institutions Collaboration Network

The collaboration network between institutions is depicted in Figure 8 and shows two distinct clusters. The red cluster is the largest and consists of five institutions, three from India and the others from China and Italy. By inspecting the publications attributed to these institutions, we can discern an emphasis on integrating technology into manufacturing systems to achieve leanness and flexibility. The second cluster in green is smaller in size and less diverse. It contains three institutions from India and one from Ethiopia. The recurring theme in the research generated by these institutions is the application of AI tools, such as deep learning and cyber-physical systems, to manufacturing systems. The Indian JSS Academy of Technical Education occupies a more central role and appears to connect this cluster with nodes in the other cluster. Inter-institutional collaboration is minimal and is primarily bound by geographical affiliation and authors' personal connections. In the case of collaborations between institutions in different countries, the prevalent observation is that one or more of the authors are expatriates in their institutions and collaborate with researchers from their native countries. There is no clear pattern of formally structured collaboration networks.

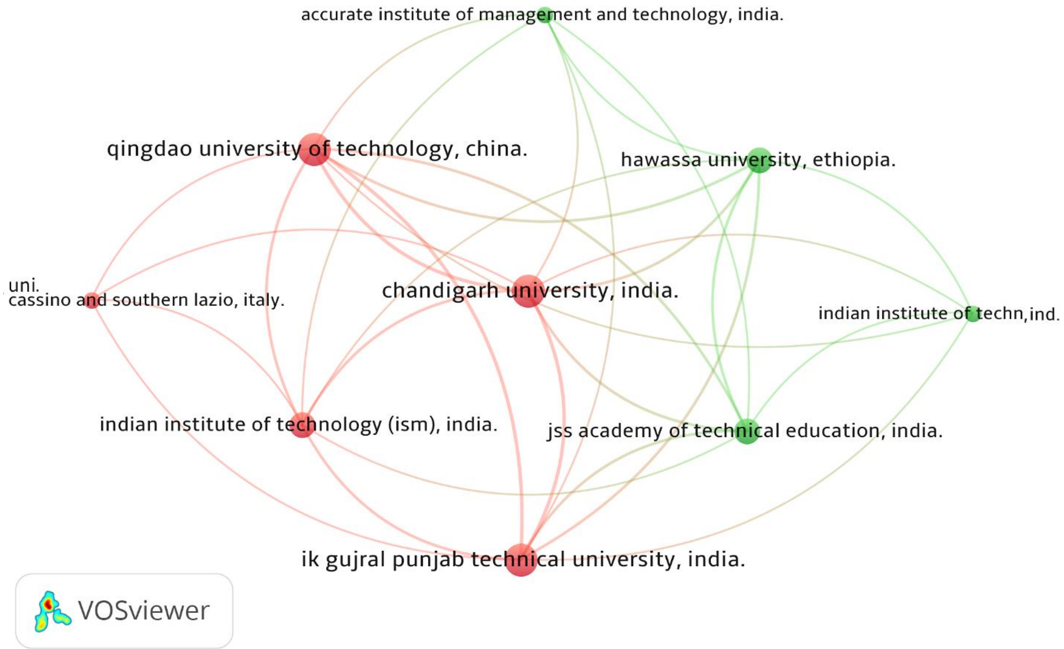

Figure 8. Collaboration network among institutions

4-9- Countries Collaboration Network

The collaboration network between nations is presented in Figure 9. There are five discernible clusters. The red cluster is the largest and contains six countries: India, China, France, Italy, Brazil, and Ethiopia. India and China stand out with more significant nodes, albeit mainly within the cluster, which reflects the well-established position of these two emerging economies in the tech industry. Outsourcing also created fertile ground for establishing production facilities in both countries that not only capitalize on cheaper labor but integrate advanced technologies to increase efficiency and lower cost, providing researchers with access to ample data to research AI in lean systems. The green cluster is the second largest among five countries: the United Kingdom, Spain, Australia, Singapore, and Hong Kong. What it lacks in size, this cluster makes up in centrality, especially the United Kingdom, which has links to most countries within and outside the cluster. The blue cluster is next with four countries: the USA, Germany, Mexico, and England*. The USA and Germany have visibly larger nodes, indicating a higher degree of collaboration; however, it is primarily within-cluster collaboration. The remaining two clusters are smaller in size and indicate a minimal scope of collaboration that is primarily internal.

Overall, there are two key observations. First, the collaboration is mainly within a single country or with countries of similar social, cultural, or economic characteristics. Examples include China and India in the first cluster and Australia, Singapore, and Hong Kong in the second cluster. Second, akin to the institutions' case, the collaboration appears to be driven mainly by researchers' personal connections and social networks and their ties with their home countries. This observation could be helpful to institutions attempting to increase international collaboration for ranking purposes or to limit the inbreeding of ideas. An increase in diversity and inclusion efforts would significantly increase collaborations across national borders.

4-10- Keywords Co-occurrence Network

Analyzing the keywords' co-occurrence network reveals the critical directions in the field by highlighting the topical priorities of the research endeavors. Figure 10 shows several color-coded clusters of keywords with, understandably, "artificial intelligence" and "lean" occupying sizeable central locations in the network. The red cluster is the largest and contains the central keyword "artificial intelligence," which bridges "machine learning" and "Industry 4.0" to various lean manifestations such as "lean 4.0", "lean production," "lean management," and "lean startup." This observation is interesting since it conveys the selective use of AI among the Industry 4.0 technologies to apply in the lean context. The

* We opted not to merge the UK and England to stay true to affiliations reported by the authors.

second is the blue cluster which is centrally located in the network and contains the "Industry 4.0" and "machine learning" keywords. It covers mainly the defining characteristics of Industry 4.0 and its various technologies, such as ML and IoT. The third significant cluster is the green one. "Lean manufacturing" appears to be the hub node and is related to "decision support systems" and "fuzzy logic" keywords. This cluster is apparently concerned with applying models and technology to address manufacturing problems. The fourth cluster is the yellow cluster with the keyword "lean" connected sparsely to "smart manufacturing" and "six sigma". This cluster is more focused on the effect of lean practices on manufacturing systems.

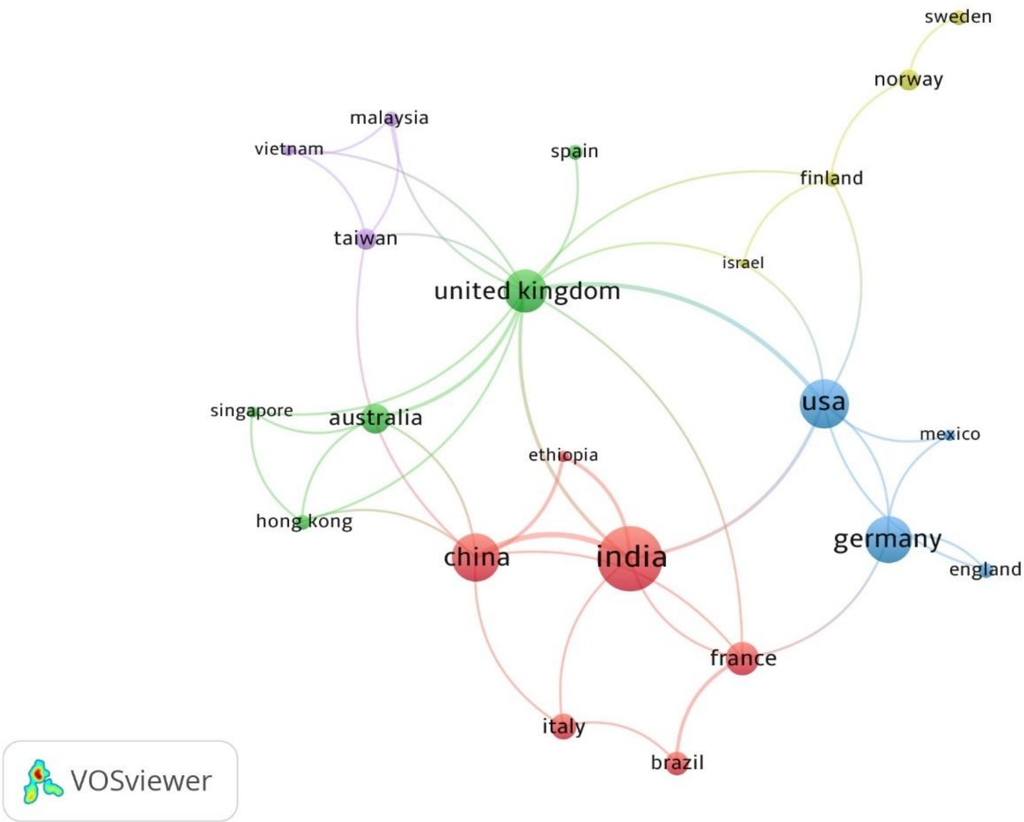

Figure 9. Collaboration network among nations producing AI in lean systems scholarly research (documents >= 2 articles)

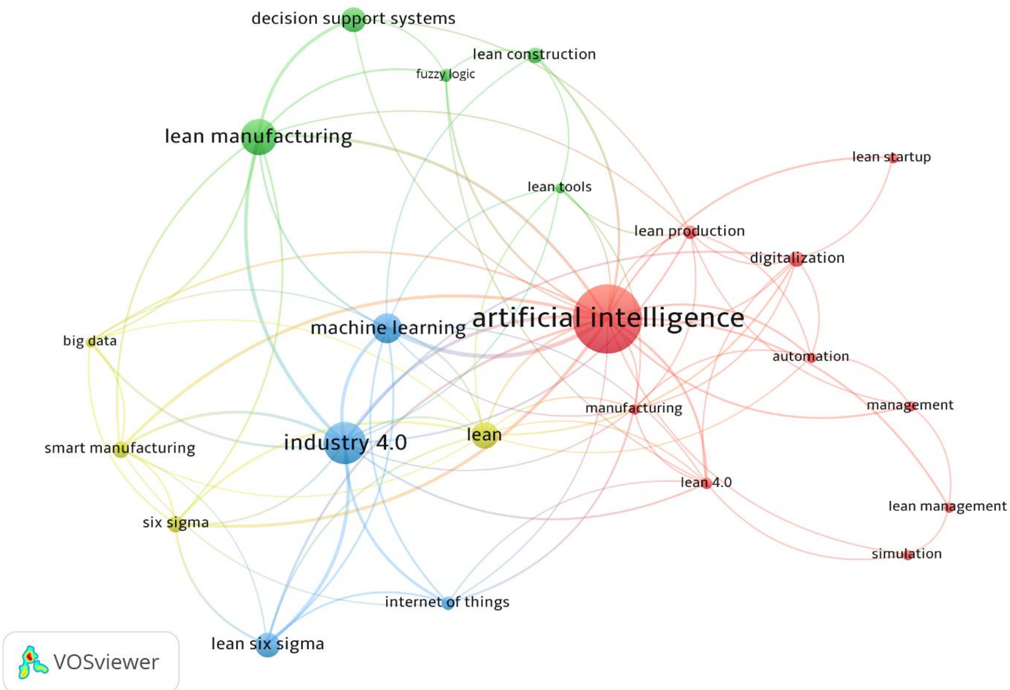

Figure 10. Co-occurrence network for author-provided AI in lean systems keywords

4-11- Trending Topics

Trending topics can be identified by investigating the presence and frequency of keywords over time. Keywords that are prominent and used more frequently indicate the importance and timeliness of a research topic. As seen in Figure 11, prior to 2019, there was an emphasis on using automation and digitization in lean production for decision-making purposes within a DSS. After 2019, the consistent use of the AI keyword with a surge in its use in 2022 marks the move towards a more structured approach to using AI and machine learning to capitalize on the technological and Big Data developments. This culminated in the coining of the “lean 4.0” term in 2023, which marks the full-fledged integration of Industry 4.0 into lean systems, which is an additional testament to the recency of the AI-lean research theme. The underlying paradigm change is a shift from systems where machines assist in making decisions to systems where machines make “lean” decisions independent of human intervention.

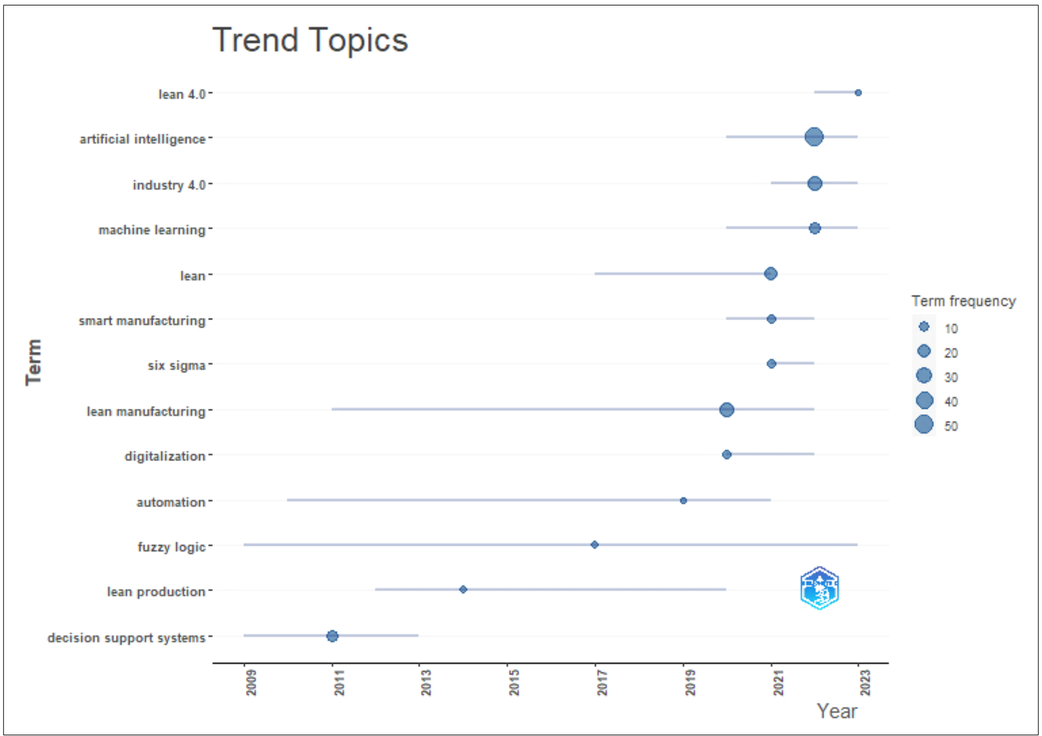

Figure 11. AI in lean systems research trending topics

4-12- Thematic Map of AI in Lean Research

A thematic map is constructed to understand the evolution of research themes better. A typical map consists of four quadrants depending on the degree of relevance (centrality) and development (density) of research topics. Note that density is a measure of links within the whole network, while centrality is a measure of interrelatedness within the network. Consequently, the top right and bottom right quadrants are characterized by high centrality, enjoying high cohesion among topics. The top right quadrant represents the “motor themes,” which are highly developed and relevant. The bottom right quadrant, on the other hand, depicts the “basic themes” that are highly relevant but not yet well developed. The two left quadrants are low on centrality, indicating that the themes are not highly interrelated. The highly developed themes represent possible “niches” for topics that may interest a smaller group of researchers. Alternatively, less developed themes may be either “emerging or declining,” depending on the development trend. From Figure 12, the top-right quadrant represents the “motor” themes that are highly relevant and significantly developed in the field and include keywords such as “artificial intelligence” and “Industry 4.0”. Note that the AI cluster is higher in development but less relevant than the “Industry 4.0” cluster. This implies that more work is needed to practically align AI with lean systems on the one hand and conceptually develop the tools and models appropriate for lean systems on the other.

The bottom-right quadrant depicts the “basic themes” that are highly relevant but have not been substantially developed. This quadrant includes “lean manufacturing” and “decision support systems” and highlights the need to develop AI-based decision-support models to manage lean systems. The top-left quadrant holds the “niche themes,” which are highly developed but have little relevance to the theme in question. This theme is typically of interest to a smaller group of researchers; however, with proper conceptual and modeling foundations relating them to lean systems, the themes may become more relevant and join the mainstream topics in the “motor themes” quadrant. The bottom-left quadrant represents the “emerging or declining themes.” It has a lower degree of relevance and development. Evidently, the “digital twin” and “lean construction” are among the emerging themes. Lean construction is argued to fall within the lean umbrella since construction can be viewed as a project, and therefore, lean construction is an instance of lean project management. The "digital twin" theme, on the other hand, is a promising technology that, if coupled with appropriate AI tools, will provide decision-makers with a flexible decision-making system that integrates the benefits of simulations into Big-Data analytics.

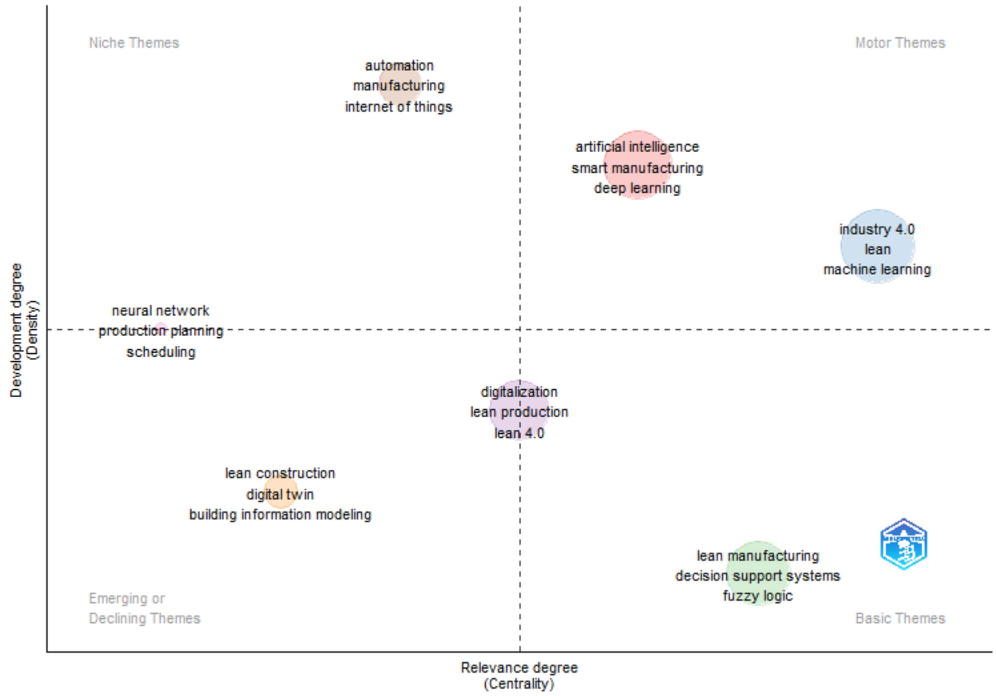

Figure 12. **AI in lean systems research thematic/strategic map**

5- Discussion

Leveraging the power of AI to propel lean systems into new realms has been the driving force behind research in this field. It has also motivated this bibliometric analysis, which provides a bird's eye view of the field to discern patterns and trends. The tremendous growth of the field, especially within the last five years, is a testament to its relevance and timeliness. However, this growth is characterized by scattered research silos with mostly dispersed, closed collaboration clusters. Most of the articles were co-authored and published in highly-ranked Q1 journals. The very low number of single-authored papers can be explained by the field's interdisciplinary nature, which integrates expertise from diverse areas such as business process analysis, mathematics, and computer science.

The research productivity on AI in lean is witnessing dramatic growth, with a surge in productivity starting in 2019. This growth is fueled by the contributions of an influential group of authors who are setting the stage for this emerging field. Intellectual and social networks unveil a scattered structure. This is striking, given that only a minority of papers are single-authored. The numerous isolated silos indicate the presence of the "homophily" effect, where impactful authors have little commonalities in the topical scope of their research and tend to collaborate with researchers of similar interests. Review papers, such as ours, play an important role in connecting fragmented networks and may point to discipline-defining potential collaborations.

By analyzing keywords, the move from developing tools for supporting human decision-making to developing systems that can autonomously make decisions in the lean systems context was identified as a key trending topic. The thematic maps further clarified the degree of relevance and development of various themes. Most themes were found to lack significantly high degrees of development, thus making a case for the need for more research in this area. Among the themes that require more work in terms of development, we identified AI-based models for decision support systems as well as lean-specific applications of Industry 4.0 and machine learning. On the other hand, themes that were deemed less relevant included automation and digital twins. With proper conceptual justification and model adaptation, these themes may prove worthwhile in pushing the research frontiers in the AI-lean domain.

The rapid advancements in AI and Industry 4.0 technologies may lead to changes in trending topics or those that require further development. In particular, recent studies look into broader and more exhaustive integration of AI tools and lean concepts [77]. Furthermore, there will be a move towards including more elements of the supply chain in the integrated system [78] since the focus until now has been on improving predictive capabilities. Finally, more industries and sectors will incorporate integrated AI-Lean systems into their operations as the concepts become clearer and the applications more accessible [79].

Bibliometric studies provide significant contributions to theory and practice [80]. The theoretical contributions revolve around unpacking the current theoretical state of the field and delineating its future directions. The practical contributions, on the other hand, ascertain the objective assessment of the research impact and reach to identify anomalies and provide guidance on the relative performance of various approaches to decision makers. While the potential impact of the practical implementation of AI-Lean integration could span all sectors and industries, some industries are better prepared for this integration than others. This stems from the fact that these industries have established the significant benefits that would be accrued earlier and have thus accumulated a broader and deeper understanding of the synergy achieved through integration. These industries are mainly in the manufacturing sector and include electronic components, semi-conductors, relays, and computer and automotive parts manufacturers. Nonetheless, there are few industries in the service sector that have pioneered the integration, and these include primarily construction and healthcare industries.

5-1- Theoretical Contributions

The analysis of the AI-lean research reveals four clusters: selective application of AI among the Industry 4.0 technologies to address lean systems, the defining characteristics of Industry 4.0 and its technologies, the application of technology to manufacturing problems, and the effect of lean practices on manufacturing sectors. The clusters are loosely connected, indicating the need for more integrative research. Furthermore, mapping the social patterns necessary to understand the underlying processes for supporting knowledge development indicates a “homophily” effect whereby most authors are confined to one network. For an emerging field such as AI-lean, this can reduce the speed at which standard terminology is adopted, which in turn affects knowledge discovery and sharing. Future research trends will need to address the challenges of moving from systems where machines assist in making decisions to systems where machines make “lean” decisions independently. The growing interest in “digital twins” can pave the way for such a future endeavor by investigating the potential of integrating the benefits of simulations into Big-Data analytics. The large volumes of data gathered from various IoT sensors are fed into digital twins to enable the decision-maker to better visualize the states of the system within various time frames spanning the past, present, and future. This visualization and real-time capturing of the system’s state is only feasible through the effective application of machine learning algorithms and big data analytical techniques. Digital twins have been used extensively in construction projects [45] and in the optimization of industrial processes in manufacturing, robotics, and the aviation industry [81].

5-2- Practical Contributions

The first practical contribution is the objective determination that AI integration in lean systems is exponentially growing, as evidenced by the number of publications and citations. Inspecting the various inter-institution and country collaborations reveals a concentration of the research in a small set of developed countries besides China and India and an abysmal presence of the less-developed global South economies. Strategies that could be used to reduce this chasm could include: first, a stronger effort at fostering international collaboration by establishing joint research projects between institutions in developed and developing countries can bridge the knowledge gap. As we saw in our analysis, the vast majority of the works analyzed were international. As such, such deliberate efforts at international collaborations could be imperative in increasing participation from researchers in the Global South. Second, we advocate expanding a subsidized open-access publication model, allowing researchers from less developed countries facing financial obstacles to publish in high-visibility periodicals. Third, universities and high-tech giants can establish international research hubs, allowing researchers to network and build collaborations that cross the Global North-South divide. Fourth, leading journals should advocate for international collaboration via special issues focusing on AI-Lean research in developing countries. This can also be extended to include unique conference tracks focused on AI-Lean research in emerging economies, providing visibility and a targeted avenue for researchers in these regions to share their work. Last, more calls need to be made for funding institutions to determine an equitable allocation of funds among competing research projects within the same field or across different fields. In the AI-lean context, funding priority should be given to integrative research and applied research aiming to develop “intelligent” DSS capable of making lean decisions without human intervention.

6- Conclusion

Integrating AI in lean systems is a promising venture for academics and practitioners alike. For academics, it unveils the potential of AI in addressing classically challenging lean systems problems such as scheduling and supply chain efficiency. For practitioners, it provides real-time adaptive solutions to costly production, supply, and distribution decisions within dynamic and stochastic environments. The current study identified four key clusters for theoretical investigation and highlighted the obstacles hindering a speedier convergence on unified terminology that would foster knowledge discovery and dissemination. Furthermore, the study uncovered the concentration of AI-lean research in a small number of “silos” in developed countries focused on a few select industries.

No research endeavor can be complete, and this exposition is no exception and is bounded by some important limitations. Firstly, our search used exclusively the Scopus and WoS databases due to their rigorous inclusion criteria. However, this may have reduced the sample size and excluded documents from fields that are typically under-represented in these databases. Future research might seek to expand the selection to more inclusive databases such as Google Scholar to validate or generalize our findings. Secondly, despite attempts to have a uniform definition for the term “artificial intelligence,” certain documents may use other terminology with a similar meaning or purpose. Currently, there are no formal initiatives directly aimed at unifying terminology in AI-Lean research. Bibliometric reviews, as the one we present here, are critical as they serve as an early attempt to identify terminology inconsistencies. A way to remedy those inconsistencies could be establishing a structured approach through interdisciplinary collaboration among AI, Lean, and Industry 4.0 researchers to help define and standardize key terms. This can be done through workshops, panel discussions, and papers, especially in leading conferences, and we have seen that a good portion of the work on the topic appears to be conference proceedings. As different disciplines could have adopted their own terminologies, the stronger interdisciplinary collaboration we advocate could also motivate the unification of terms. Last, reviewers and journal editors could be more involved in this effort by suggesting the utilization of a consistent set of terms. As the field matures and the terminology and keywords become more standard, future research can identify better-defined research realms.

Thirdly, most of the articles were published after 2018. The citation count for many of these articles is low due to their recency and not necessarily to their impact. This has a direct effect on the structure of the co-citation and collaboration networks. If the current publication rate is sustained, the number of eligible articles will increase significantly, providing future researchers with a more extensive dataset for other bibliometric analyses or structured reviews. Building on this last point, our study did not include publications in practitioner-oriented and industry outlets. Future researchers might want to cast a wider net and include those sources, as science has always suffered from a research-practice gap, and the incorporation of such sources could enrich our understanding of AI in lean systems. Fourth, we have opted to limit our data to documents written in English or for which English versions have been published. Given that a lot of the work in the area has been done in China and India, there is a possibility that articles published in other languages were missed. Since this work reviews academic peer-reviewed work, this issue might be overestimated, as most researchers publish using English, which constitutes the lingua franca in most academic spheres. Finally, there are several gaps resulting from the different topic-technology combinations (Table 1), which present fertile ground for studies that will connect the various research silos together. These venues will undoubtedly enrich the understanding of AI’s impact on business operations and our lives in general.

7- Declarations

7-1- Author Contributions

Conceptualization, N.S. and A.E.; methodology, A.E., R.A., and N.S.; software, A.E. and R.A.; validation, N.S., A.E., and R.A.; formal analysis, N.S. and A.E.; investigation, A.E. and R.A.; resources, N.S.; data curation, A.E. and R.A.; writing—original draft preparation, N.S.; writing—review and editing, N.S., A.E., and R.A.; visualization, A.E. and R.A.; supervision, N.S.; project administration, N.S.; funding acquisition, N.S. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The APC for this article are provided with the support of the Gulf University for Science and Technology through a Q1APC grant.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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