BIBLIOMETRIC REVIEW ON DATA ANALYTICS IN LEAN-DECISION SUPPORT SYSTEM DEVELOPMENT BASED ON SCOPUS DATABASE

N.A.Q.M Shafee[1], E. Mohamad[1], M.S.A. Rahman[1], I. Teruaki[2]

[1]Fakulti of Industrial and Manufacturing Technology and Engineering,
Universiti Teknikal Malaysia Melaka, Malaysia.

[2]Faculty of Computer science and systems engineering,
Okayama prefectural university, Japan.

*Corresponding Author's Email: effendi@utem.edu.my

Article History: Received xxxxx; Revised xxxx; Accepted xxxx

ABSTRACT: The rapid development of industry 4.0 has significantly accelerated the advancement of decision support system (DSS) specifically, in the lean manufacturing sector. This study explores the integration of data analytics (DA) within the development of lean-DSS, motivated by the necessity for academic insights into creating more efficient and effective systems. By conducting a bibliometric review based on the Scopus database, this research identifies the key trends, methodologies, and gaps in the current literature. The findings have led to the creation of a novel framework, iDSS-ProLean, which has been successfully registered with the UTeM innovation department and presented with positive results. This framework serves as a blueprint for future DSS development, offering a structured approach to enhance the decision-making processes in lean manufacturing environments.

KEYWORDS: *decision support system framework, data analytics, lean manufacturing, bibliography review, Scopus database*

1.0 INTRODUCTION

The advent of Industry 4.0 in 2011 marked a significant turning point in the manufacturing sector by integrating advanced technologies [1]. This revolution drove the need for more sophisticated DSS to enhance operational efficiency and competitiveness, particularly benefiting lean manufacturing, which focuses on minimizing waste and maximizing value. Coupling DSS with DA provides a robust framework for real-time decision-making and continuous improvement in lean environments [2]. The rapid technological development necessitates a comprehensive academic perspective on the evolution and impact of DSS in lean manufacturing [3].

This bibliometric review aims to analyze existing literature on DSS and DA drawing insights from the Scopus database. By examining trends, methodologies, and research gaps, this study seeks to understand how DSS has evolved with DA since Industry 4.0's inception and proposes a novel framework, iDSS-ProLean, to guide future DSS development in manufacturing.

2.0 METHODOLOGY

To address the research questions, this study employed a bibliometric analysis methodology, as advocated by various scholars, to scrutinize research trends in DSS and DA within lean manufacturing. Data extraction was conducted using the Scopus database, recognized as the largest indexer of global research content, encompassing titles from over 5,000 publishers worldwide. The search query used was: `TITLE ("decision support system" OR "DSS" OR "data analytics" OR "DA" OR "lean manufacturing" OR "LM") AND TITLE ("development" OR "lean production line" OR "development")`, which yielded 346 articles post-initial document screening.

Further screening involved a manual review of abstracts and full texts to eliminate duplicates and irrelevant articles, resulting in the selection of the top 50 highly cited articles. This rigorous screening process ensured the inclusion of studies with high relevance, methodological rigor, and significant impact on the field. The earliest publication dated back to 2011, highlighting the utilization of DSS for lean tools selection in the USA. By focusing on publications from 2011 onwards, this study captures the evolution and integration of DSS and DA in the context of Industry 4.0 and lean manufacturing.

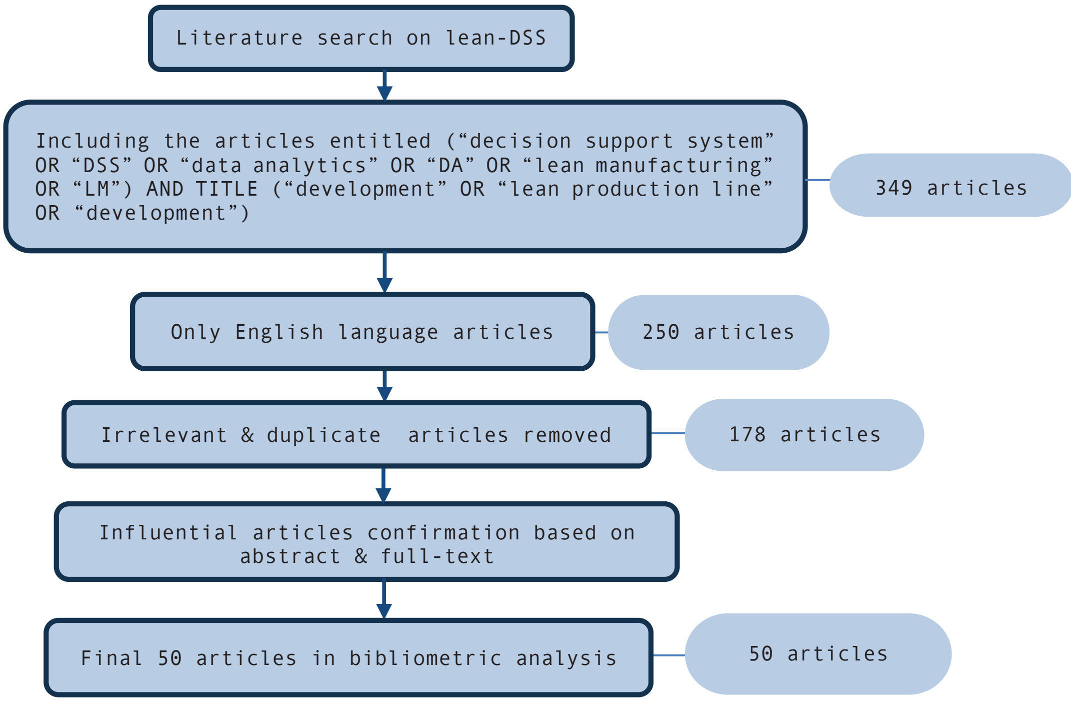

Figure 1 Bibliography Flow Chart

The selected 50 articles were analyzed using bibliometric indicators such as citation analysis, co-authorship networks, and keyword co-occurrence to identify key trends, methodologies, and research gaps.

3.0 RESULTS

The bibliometric analysis conducted in this study yielded several key insights into the development and integration of DSS and DA within the lean manufacturing sector since the advent of Industry 4.0 in 2011.

3.1 Key Trends and Methodologies

The analysis identified a significant increase in publications related to DSS and DA in lean manufacturing, particularly after 2015. This surge aligns with the growing emphasis on Industry 4.0 technologies and their applications in manufacturing [4]. The highly cited articles focused on the integration of IoT, big data, and artificial intelligence within DSS frameworks to enhance lean manufacturing processes.

3.2 Research Gaps

Despite the wealth of research, several gaps were identified. Notably, there is a limited exploration of real-time data integration from IoT devices into DSS for dynamic decision-making [5-8]. Additionally, while there are studies addressed specific aspects of lean manufacturing, such as waste reduction and process optimization, few offered comprehensive frameworks that integrate multiple lean tools and technologies. The top 50 highly cited articles contributed significantly to the field by providing foundational theories, robust empirical evidence, and innovative methodologies. These articles collectively advanced the understanding of how DSS and DA can be leveraged to achieve lean manufacturing goals.

Table 1: Summary of Bibliometric Analysis Results [9-15]

ASPECTS	KEY FINDINGS
Publi-cations trends	Significant increase in publications post-2015, aligning with Industry 4.0 advancements
Most famous methodology	Empirical case studies, simulation models, and framework development are the predominant methodologies
Research gaps	Limited exploration of real-time data integration from IoT devices into DSS for dynamic decision-making. Few comprehensive frameworks integrating multiple lean tools and technologies
Top contri-butions	Foundational theories, robust empirical evidence, and innovative methodologies from the top 50 highly cited articles
Novel framework	Developed a novel framework integrating advanced DA with DSS, registered with UTeM Innovation Department. Incorporates value stream mapping, Kanban, and SMED. Received positive feedback as a blueprint for future DSS development

3.3 DA Integration Challenges

Research gaps in the coupling of DA with DSS for lean manufacturing highlight the need for advanced integration techniques and seamless interoperability. Addressing these issues are essential for reliable DSS outputs and improved decision-making. By filling these gaps, future studies can significantly optimize manufacturing processes and enhance productivity. Table 2 below shows the challenges in through integration.

Table 2 the challenges of the DA integration [15-21]

Challenges	Description
Advance algo-rithms	Research should explore the techniques that can analyze historical data, predict future outcomes, and recommend optimal actions
Interoperability	Ensuring that data can flow seamlessly between IoT devices, analytics platforms, and DSS requires the development of standardized protocols and middleware solutions that bridge these gaps
Data quality & security	High-quality data is crucial for effective analytics. Research is needed to develop advanced data cleansing and validation techniques that ensure data accuracy, completeness, and consistency
Scalability and Flexibility	As manufacturing operations grow, the volume of data generated increases exponentially. Research is required to develop scalable DSS architectures that can handle large data volumes without performance degradation. This includes leveraging cloud computing and distributed processing techniques.

4.0 DISCUSSION

4.1 Development of a Novel Framework

The findings from this bibliometric analysis informed the development of a novel framework designed to enhance decision-making in lean manufacturing environments. This framework, now registered with the UTeM Innovation Department, integrates advanced DA with DSS to provide real-time, actionable insights. It able to incorporate multiple lean tools, including Kanban and SMED within a cohesive system. The framework has been presented and received positive feedback, establishing it as a blueprint for future Lean-DSS development. This framework's structured approach aims to harness the full potential of Industry 4.0 technologies.

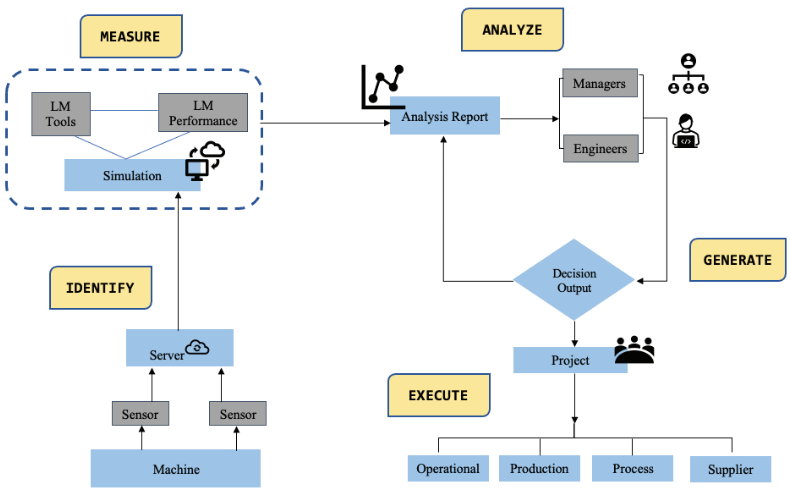

Figure 2 the Registered iDSS-ProLean framework

The iDSS-ProLean framework's efficacy in supporting decision-making within lean manufacturing is underscored by its alignment with core lean principles through five distinct phases: Identify, Measure, Analyse, Generate, and Execute. Each phase contributes uniquely to a systematic examination of processes, facilitating informed decision-making and ensuring continuous evaluation and improvement. This structured approach adheres to the lean philosophy of continuous improvement.

A pivotal aspect of the framework is its integration of DA, particularly in the Measure phase, where lean tools and performance metrics analyze data to provide insights into process efficiency and identify areas for enhancement. The framework's utilization of sensors for direct data retrieval ensures accuracy and minimizes human error, streamlining data collection and processing. This automation enhances operational efficiency and aids engineers and managers in forecasting whether inputs can meet daily demand, thereby enabling timely and reliable decision-making.

4.2 The Advancements through Data Analytics (DA)

The integration of DA into this iDSS-ProLean framework holds significant promise for advancing DSS in this domain [22, 23]. Real-time monitoring and analysis of IoT sensor data offer valuable insights into process dynamics and equipment performance, enabling proactive decision-making and process optimization [24]. Next, is the predictive maintenance that based on historical data and analytics helps prevent equipment failures, reducing downtime and maintenance costs [25-27]. Then, process optimization through DA also identifies patterns and trends, allowing for the fine-tuning of process parameters to enhance efficiency and quality [26]. Subsequently, anomaly detection capabilities enable early identification of deviations from normal operation, facilitating timely corrective actions [27]. Moreover, data-driven decision support provides actionable insights, guiding operators in adjusting process parameters and predicting the consequences of different decisions [28, 29]. Following this, performance monitoring using DA tracks key performance indicators (KPIs), providing a comprehensive view of process performance and highlighting areas for improvement [30]. Overall, the integration of DA into the iDSS-ProLean framework enhances the lean manufacturing efficiency through the enhancement of the decision-making abilities.

5.0 CONCLUSION

Despite the advancements in lean techniques, comprehensive DSS frameworks integrating these methods are underdeveloped. To address this, the iDSS-ProLean framework is being conceptualized as a blueprint for future lean-DSS applications in which provides a structured approach to integrating lean methodologies into DSS, enhancing decision-making and optimizing manufacturing processes. By leveraging DA and IoT, it creates a dynamic, adaptive system for evolving manufacturing needs. This development advances DSS application in lean manufacturing, aiming to achieve lean objectives like waste reduction and improved flow, ultimately supporting continuous improvement and competitiveness in the sector.

ACKNOWLEDGEMENT

The authors are grateful to the Malaysian Government and Universiti Teknikal Malaysia Melaka (UTeM) for funding this research via Grant (FRGS/1/2020/TK0/UTEM/02/42), and all group members and their wonderful efforts to produce the outcomes of the research.

REFERENCE

[1] H. Fatorachian and H. Kazemi, "Impact of Industry 4.0 on supply chain performance", *Production Planning & Control*, vol. 32, pp. 63 – 81, 2020.

[2] S. Bag, S. Gupta and S. Kumar, "Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development", *International Journal of Production Economics,* vol. 231, pp. 107844, 2021.

[3] C. Bai, P. Dallasega, G. Orzes, and J. Sarkis, "Industry 4.0 technologies assessment: A sustainability perspective." *International Journal of Production Economics,* vol. 229, pp. 107776, 2020.

[4] T. Zheng, M. Ardolino, A. Bacchetti and M. Perona, "The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review", *International Journal of Production Research,* vol. 59 pp. 1922 – 1954, 2020.

[5] A. Saoud and A. Bellabdaoui, "DSS design for carrier collaboration using Big graph & IOT." 2018 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA), pp. 211-215, 2018.

[6] M. Syafrudin, G. Alfian, N. L. Fitriyani and J. Rhee, "Performance analysis of iot-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing", *Sensors (Basel, Switzerland*), pp. 18, 2018.

[7] T. Coito, M. Martins, J. Viegas, Bernardo Firme, J. Figueiredo, S. Vieira and J. Sousa, "A Middleware Platform for Intelligent Automation: An Industrial Prototype Implementation", *Comput. Ind.,* vol. 123, pp. 103329, 2020.

[8] T. Coito, M. Martins, J. Viegas, Bernardo Firme, J. Figueiredo, S. Vieira and J. Sousa, "A middleware platform for intelligent automation: an industrial prototype implementation", *Comput. Ind.,* vol. 123, pp. 103329, 2020.

[9] T. Ito, M. S. Abd Rahman, E. Mohamad, A. A. Abdul Rahman and M. Salleh, "Internet of things and simulation approach for decision support system in lean manufacturing", *Journal of Advanced Mechanical Design, Systems, and Manufacturing, 2020.*

[10] S. KuikS., and L. Diong, "A model-driven decision approach to collaborative planning and obsolescence for manufacturing operations", *Industrial Management and Data System*, vol. 119, pp. 1926-1946, 2019.

[11] A.Omidkar, A. Khalili, H. Nguyen and H. Shafiei, "Reinforcement-learning-based resource allocation for energy-harvesting-aided d2d communications in iot networks", *IEEE Internet of Things Journal,* Vol. 9, pp.16521-16531, 2020.

[12] M. Ramadan, B. Salah, M. Othman and A. A. Ayubali, "Industry 4.0-Based Real-Time Scheduling and Dispatching in Lean Manufacturing Systems." *Sustainability* (2020).

[13] Ndrecaj, V., Hashim, M., Mason-Jones, R., Ndou, V., and I. Tlemsani, "exploring lean six sigma as dynamic capability to enable sustainable performance optimisation in times of uncertainty", *Sustainability*, 2023.
[14] A. Chiarini and M. Kumar, "Lean Six Sigma and Industry 4.0 integration for Operational Excellence: evidence from Italian manufacturing companies." *Production Planning & Control,* vol. 32 pp. 1084 – 1101, 2020.
[15] M. Rahman, E. Mohamad, E., and A. Rahman, "Enhancement of overall equipment effectiveness (OEE) data by using simulation as decision making tools for line balancing", *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 18, pp. 1040-1047, 2020.
[16] S. Albliwi, J. Antony and S. A. Halim-Lim,"A systematic review of Lean Six Sigma for the manufacturing industry", *Business Process Management Journal,* vol. 21, pp. 665-691, 2015.
[17] J. Shruti Raval, R. Kant and R. Shankar, "Revealing research trends and themes in Lean Six Sigma: from 2000 to 2016", *International Journal of Lean Six Sigma*, 2018.
[18] S. Gupta, S., Modgil and A. Gunasekaran, "Big data in lean six sigma: a review and further research directions", *International Journal of Production Research*, vol.58, pp. 947 – 969, 2020.
[19] L. Evangelos, L. Psomas and J. Antony, "Research gaps in Lean manufacturing: a systematic literature review", *International Journal of Quality & Reliability Management,* 2019.
[20] A. Chiarini and M. Kumar, "Lean Six Sigma and Industry 4.0 integration for Operational Excellence: evidence from Italian manufacturing companies", *Production Planning & Control*, vol.32, pp. 1084 – 1101, 2020.
[21] Y. Goshime, D., Kitaw, D., and K., Jilcha, "Lean manufacturing as a vehicle for improving productivity and customer satisfaction", International Journal of Lean Six Sigma, 2019.
[22] M. Rahman, M., Mohamad, E., and A. Rahman, "Development of IoT—enabled data analytics enhance decision support system for lean manufacturing process improvement. Concurrent Engineering, vol. 29, pp. 208 – 220, 2021.
[23] M. Syafrudin, G. Alfian, N. L.Fitriyani and J. Rhee, "Performance analysis of iot-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing", *Sensors (Basel, Switzerland),* vol.18, 2018.
[24] Q. Jing Zou, Q. Chang, Y. Lei and J. Arinez, "Production System Performance Identification Using Sensor Data*", IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, pp. 255-264, 2018.
[25] M. Bhatia and S. Sood, "Quantum Computing-Inspired Network Optimization for IoT Applications." *IEEE Internet of Things Journal*, vol. 7, pp. 5590-5598, 2020.
[26] M. Uppal, D., Gupta, S., Juneja, A., Sulaiman, K., Rajab, A., Rajab, A., M. Elmagzoub, A., and Shaikh, "Cloud-Based Fault Prediction for Real-Time Monitoring of Sensor Data in Hospital Environment Using Machine Learning. Sustainability, 2020.
[27] H. Y. Teh, A. Kempa-Liehr and K. Wang, "Sensor data quality: a systematic review." *Journal of Big Data*, vol. 7, pp. 1-49, 2020.
[28] M. Ghahramani, Y. Qiao, M. Zhou, A. O'Hagan and J.Sweeney, "AI-based modeling and data-driven evaluation for smart manufacturing processes", *IEEE/CAA Journal of Automatica Sinica,* vol. 7, pp. 1026-1037, 2020.
[29] W. Chen, "Intelligent manufacturing production line data monitoring system for industrial internet of things." *Comput. Commun.*, vol. 151, pp. 31-41, 2020.
[30] Y. Fathy, M. Jaber and A. Brintrup, "Learning with imbalanced data in smart manufacturing: a comparative analysis", *IEEE Access,* vol. 9, pp. 2734-2757, 2021.