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Predictive waste management in SMEs through lean manufacturing and machine learning

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ABSTRACT

This study examines the integration of Lean Manufacturing (LM) and Machine Learning (ML) for waste prediction and production process optimization in Small and Medium Enterprises (SMEs) in the digital era. The study employed a Systematic Literature Review (SLR) approach following the PRISMA framework by analyzing publications retrieved from Scopus, Web of Science, ScienceDirect, IEEE Xplore, Google Scholar, and national accredited journal databases. The review focused on studies published within the last ten years and applied explicit inclusion and exclusion criteria. From an initial pool of 485 records, 15 studies were selected for final analysis. Data were synthesized using thematic analysis to identify key themes, integration mechanisms, benefits, and implementation challenges associated with Lean Manufacturing and Machine Learning integration. The findings revealed five dominant themes: waste identification and reduction, predictive analytics and forecasting, production process optimization, implementation barriers in SMEs, and digital transformation readiness. The review indicates that Lean Manufacturing contributes to the systematic identification and elimination of operational waste through continuous improvement practices, while Machine Learning enhances predictive capabilities through data-driven analysis, real-time monitoring, and early detection of operational inefficiencies. The synthesis further suggests that integrating LM and ML may enable SMEs to shift from reactive waste management toward more predictive and proactive production management. However, several implementation barriers were identified, including limitations in human resources, technological infrastructure, data availability, and organizational readiness. This study contributes a conceptual framework explaining the theoretical mechanisms linking LM and ML in SME production systems. The framework highlights how predictive analytics can support waste reduction, process optimization, and digital transformation initiatives. Nevertheless, the findings are derived from literature synthesis rather than primary empirical evidence and therefore require further validation through future case studies, surveys, and industrial implementation projects.

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Introduction

Based on previous studies, research on Lean Manufacturing (LM) has primarily focused on improving production efficiency through waste identification, process standardization, and continuous improvement practices. In contrast, studies on Machine Learning (ML) have largely emphasized predictive analytics, real-time monitoring, and data-driven optimization in manufacturing environments. Although both approaches aim to improve operational performance, they rely on different mechanisms. Lean Manufacturing focuses on eliminating non-value-added activities through systematic process improvement, whereas Machine Learning utilizes data patterns and predictive algorithms to anticipate operational problems before they occur. These characteristics suggest a complementary relationship in which Lean Manufacturing provides the operational framework for waste reduction, while Machine Learning enhances decision-making through predictive intelligence. Recent studies have highlighted the potential benefits of integrating digital technologies with manufacturing improvement practices. Weichert et al. (2019) demonstrated that Machine Learning can significantly improve production process optimization through predictive analysis and early detection of operational inefficiencies. Similarly, Mittal et al. (2020) emphasized the importance of digital technologies in supporting smart manufacturing initiatives. More recently, Panigrahi et al. (2023) and Alhakimi (2024) suggested that integrating intelligent technologies with lean principles can enhance operational responsiveness, production efficiency, and organizational adaptability. However, most existing studies have been conducted within large manufacturing organizations and Industry 4.0 environments, whereas investigations focusing specifically on SMEs remain comparatively limited.

Beyond this contextual limitation, the literature also reveals a significant theoretical and methodological gap. Existing studies generally examine Lean Manufacturing and Machine Learning as separate streams of research, employ different performance indicators, and adopt distinct analytical frameworks. Consequently, there is limited understanding of how predictive analytics can systematically support lean waste-reduction activities, continuous improvement initiatives, and production optimization processes within SME environments. Furthermore, previous studies rarely provide an integrated conceptual explanation of the mechanisms linking Machine Learning capabilities such as forecasting, anomaly detection, and predictive analytics with Lean Manufacturing practices, including waste identification, process standardization, and continuous improvement. As a result, the theoretical pathways through which Machine Learning can strengthen Lean Manufacturing implementation remain insufficiently articulated.

This limitation is particularly important in the context of SMEs, which often face unique constraints related to financial resources, technological infrastructure, data availability, and technical expertise (Jia & Puvanasvaran, 2020; Kaiser et al., 2023). These constraints influence the feasibility of adopting advanced digital technologies and reduce the applicability of integration models originally developed for large-scale manufacturing organizations. Therefore, there is a need for a comprehensive synthesis of existing knowledge to identify the critical factors, implementation barriers, enabling conditions, and integration mechanisms that can support the adoption of Lean Manufacturing and Machine Learning in SME production systems.

The novelty of this study lies in its systematic synthesis of Lean Manufacturing and Machine Learning literature from an SME perspective. Unlike previous studies that primarily examined lean practices or Machine Learning applications independently, this study integrates insights from both streams of literature to develop a conceptual framework that explains how predictive analytics can support waste prediction, production process optimization, and continuous improvement activities. Through a systematic literature review approach, the study identifies recurring themes, theoretical relationships, implementation barriers, and potential operational outcomes associated with Lean–Machine Learning integration. In doing so, the study contributes a structured conceptual understanding of how SMEs can leverage digital technologies to enhance operational performance and support digital transformation initiatives.

Accordingly, this study aims to (1) analyze the theoretical relationships between Lean Manufacturing principles and Machine Learning capabilities in waste management and production optimization, (2) identify the critical barriers and enabling factors affecting their integration in SMEs, (3) synthesize the key themes and integration mechanisms reported in previous studies, (4) develop a conceptual framework for Lean Manufacturing and Machine Learning integration in SME production systems, and (5) formulate practical recommendations for implementing the proposed framework in resource-constrained SME environments. Through these objectives, the study contributes to the advancement of operations management and digital manufacturing literature by providing a theoretically grounded synthesis that can serve as a foundation for future empirical validation and implementation studies in SME contexts.

Method

This study employed a qualitative approach using a Systematic Literature Review (SLR) method to examine the integration of Lean Manufacturing and Machine Learning in predicting waste and optimizing production processes within Small and Medium Enterprises (SMEs). The review process followed the evidence-based management framework proposed by Tranfield et al. (2003) and was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure transparency, rigor, and reproducibility. The systematic review approach was selected because it enables the identification, evaluation, and synthesis of existing knowledge from diverse sources, thereby facilitating the development of a comprehensive conceptual understanding of the research topic (Tranfield et al., 2003).

The data used in this study consisted of secondary sources obtained from peer-reviewed journal articles, conference proceedings, academic books, and research reports relevant to Lean Manufacturing, Machine Learning, waste reduction, predictive analytics, production optimization, and SME operations. Literature searches were conducted through several scientific databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, Google Scholar, and national accredited journal portals. The search process employed predefined keywords and Boolean operators such as "Lean Manufacturing," "Machine Learning," "waste reduction," "predictive analytics," "production optimization," and "SMEs." To ensure the relevance and currency of the reviewed literature, the search primarily focused on publications published within the last ten years, reflecting recent developments in digital technologies and smart manufacturing systems (Caldera et al., 2019).

To ensure methodological rigor, explicit inclusion and exclusion criteria were established. The inclusion criteria comprised studies that discussed Lean Manufacturing, Machine Learning, or their integration within manufacturing contexts; addressed waste reduction, process optimization, predictive analytics, or production efficiency; were published in peer-reviewed journals or recognized academic publications; and were available in English or Bahasa Indonesia. Conversely, publications unrelated to manufacturing systems, non-academic documents such as editorials or opinion papers, duplicate records, studies lacking sufficient methodological information, and publications with inaccessible full-text versions were excluded from the review. The literature selection process followed the PRISMA stages of identification, screening, eligibility assessment, and final inclusion (Page et al., 2021).

The initial search identified 485 records across all databases. Following the PRISMA procedure, 71 duplicate records, 43 non-peer-reviewed publications, and 11 publications that did not meet the language criteria were removed, leaving 360 records for title and abstract screening. During the screening stage, 282 records were excluded because they were not directly related to Lean Manufacturing, Machine Learning, waste prediction, production optimization, or SME applications. Consequently, 78 studies were retained for full-text retrieval. However, 14 articles could not be retrieved in full text and were therefore excluded from further analysis. Subsequently, 64 full-text articles were assessed for eligibility based on the predefined inclusion and exclusion criteria. Among these studies, 21 articles were excluded because they did not specifically address Lean Manufacturing–Machine Learning integration, 13 articles did not focus on manufacturing or SME contexts, 9 articles lacked sufficient methodological information, and 6 articles contained incomplete findings or overlapping evidence. As a result, 15 studies were included in the final qualitative synthesis and comparative analysis. The complete literature selection process is illustrated in the PRISMA flow diagram (Page et al., 2021).

Following the selection process, relevant information was extracted from each publication using a structured data extraction protocol. The extracted information included author details, publication year, research objectives, industrial context, Lean Manufacturing practices, Machine Learning techniques, reported outcomes, implementation challenges, and recommendations for future research. The analysis employed a thematic content analysis approach using a combination of deductive and inductive coding strategies. Deductive coding was based on established theoretical constructs from Lean Manufacturing and Machine Learning literature, including waste reduction, continuous improvement, predictive analytics, process optimization, decision support systems, and digital transformation. Inductive coding was subsequently applied to capture emerging themes and insights that were not covered by the initial coding framework (Braun & Clarke, 2006).

To enhance analytical reliability, the coding process was independently conducted by two researchers, and inter-coder agreement was assessed using Cohen's Kappa coefficient. Any discrepancies in coding were discussed and resolved through consensus to ensure consistency in interpretation. The analysis proceeded through three stages: data reduction, data display, and interpretation. During data reduction, relevant studies were selected and categorized according to the coding framework. Subsequently, the extracted information was organized into thematic categories, including Lean Manufacturing principles, Machine Learning applications, integration mechanisms, implementation barriers, and critical success factors for SMEs. Finally, the reviewed findings were interpreted through a thematic synthesis process to identify recurring patterns, converging evidence, and inconsistencies across studies. Contradictory findings were carefully examined by considering differences in industrial contexts, methodological approaches, and implementation conditions (Tranfield et al., 2003).

Thematic saturation was considered achieved when no additional themes, barriers, integration mechanisms, or success factors emerged from the reviewed literature. The final synthesis was used to develop a conceptual framework explaining how Lean Manufacturing and Machine Learning can be integrated to support waste prediction and production process optimization in SMEs. To ensure trustworthiness, the study adopted several quality assurance strategies, including transparent documentation of search procedures, systematic coding protocols, triangulation of evidence from multiple databases, and comprehensive reporting of the review process (Lincoln & Guba, 1985). Through this systematic and rigorous approach, the study aims to provide a reliable conceptual foundation for understanding the role of Lean Manufacturing and Machine Learning integration in enhancing operational efficiency and supporting digital transformation within SME environments.

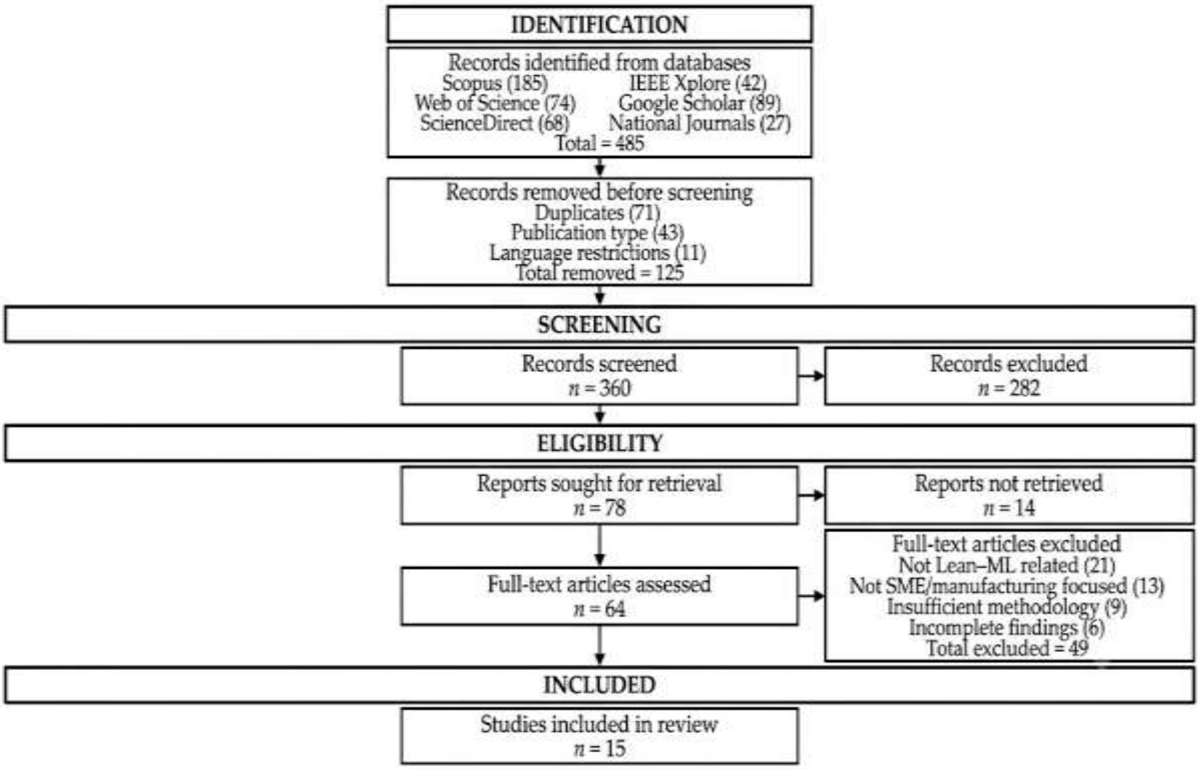

Figure 1 <PRISMA 2020 Flow Diagram Illustrating the Selection of Studies Included in the Systematic Literature Review>

Results and Discussions

Literature Selection Results

The systematic literature review was conducted following the PRISMA procedure described in the methodology section. The initial database search identified 485 publications from Scopus, Web of Science, ScienceDirect, IEEE Xplore, Google Scholar, and national journal databases. After removing duplicate records and applying title and abstract screening, 64 studies remained for full-text assessment. Following the application of the inclusion and exclusion criteria, 15 studies were selected for final analysis. The selected studies covered various topics related to Lean Manufacturing, Machine Learning, Industry 4.0, production optimization, predictive analytics, waste reduction, and SME operational performance. The complete selection process is illustrated in the PRISMA flow diagram.

To ensure analytical consistency, all selected articles were coded using a thematic framework developed from the literature and refined through iterative analysis. The coding process generated five dominant themes: waste identification and reduction predictive analytics and forecasting production process optimization implementation barriers in SMEs and digital transformation readiness.

Comparative Analysis of Selected Studies

Table 1 presents a comparative analysis of the fifteen studies included in the review. The studies vary considerably in terms of methodological approach, industrial context, and analytical focus. While several studies focused on Lean Manufacturing as a waste-reduction strategy (Hassan et al., 2013; Grewal et al., 2008; Derlini & Siagian, 2025), others emphasized Machine Learning applications for predictive analytics and operational optimization (Weichert et al., 2019; Kaiser et al., 2023; Makhanya et al., 2023).

More recent studies have begun exploring the integration of Lean Manufacturing and Machine Learning. For example, Mendoza-Sotomayor et al. (2024) reported a 42.4% reduction in quality control time and a 33.3% improvement in operational efficiency through Lean–ML integration. Similarly, Yuphin and Ruanchoengchum (2020) observed a 74% increase in production efficiency and a 10% reduction in turnaround time. These findings indicate that combining Lean Manufacturing with Machine Learning may generate greater operational benefits than implementing either approach independently.

However, the comparison also reveals several limitations in the existing literature. Most integration studies have been conducted in large manufacturing organizations, healthcare systems, or simulation environments, whereas SME-focused empirical studies remain relatively scarce. Furthermore, many studies evaluate Lean Manufacturing and Machine Learning separately, resulting in fragmented theoretical frameworks and inconsistent performance measures.

Table 1 <Comparative Analysis of Previous Studies on Lean Manufacturing, Machine Learning, and Production Optimization>

Author(s)	Method	Sample/ Context	Main Findings	Contribution	Limitation
Jordan, Dossou, & Chang (2019)	Lean Manufacturing and Machine Learning Framework	Hospital logistics and medicine procurement	The integration of Lean Manufacturing and Machine Learning improved procurement planning, inventory control, and lead-time management.	One of the earliest studies combining Lean and ML principles for operational improvement.	Focused on healthcare logistics rather than manufacturing environments.
Mendoza-Sotomayor et al. (2024)	Case Study	Beverage manufacturing industry	Reduced quality control time by 42.4% and increased operational efficiency by 33.3% through Lean–ML integration.	Demonstrated practical implementation of Lean–ML integration in production systems.	Findings are limited to a single industrial case.
Makhanya et al. (2023)	CART Machine Learning Model	Manufacturing company (215,924 observations)	Machine learning predicted production waste with 97.31% accuracy.	Developed a highly accurate predictive waste-management model.	Relied solely on quantitative secondary data.
Cruz et al. (2024)	AutoML and Multi-Objective Optimization	Small manufacturing enterprise (SME)	Increased productivity by 3.19% and reduced defect rates by 2.15%.	Demonstrated the feasibility of AutoML for SME production optimization.	Validation was limited to a single SME case.
Paraschos et al. (2024)	Reinforcement Learning Simulation	Smart manufacturing systems	Reinforcement Learning improved sustainable and lean production decisions.	Introduced intelligent decision-support mechanisms for Lean 4.0 environments.	Results were simulation-based and lacked large-scale industrial validation.

Author(s)	Method	Sample/ Context	Main Findings	Contribution	Limitation
Sumi (2025)	PRISMA-Based Systematic Literature Review	47 Lean–ML studies	Hybrid ML approaches outperformed individual algorithms in production optimization.	Proposed a Lean 4.0 integration framework.	Limited evidence regarding SME implementation.
Nwamekwe et al. (2025)	Literature Review	Smart factories	AI enhanced Lean Manufacturing and Six Sigma through predictive analytics and real-time monitoring.	Highlighted AI's role in supporting continuous improvement initiatives.	Conceptual review without empirical testing.
Daryono et al. (2025)	PLS-SEM	110 Indonesian textile MSMEs	Smart Value Stream Mapping and digitalization significantly reduced environmental waste.	Empirically validated digital-lean integration in MSMEs.	Focused mainly on environmental waste reduction.
Ahmad & Abbas (2025)	Conceptual Study	SMEs and waste management	AI predicted waste-generation patterns and improved resource efficiency.	Extended AI applications to waste valorization in SMEs.	No empirical validation provided.
Derlini & Siagian (2025)	Literature Review	Indonesian SMEs	Lean implementation improved production efficiency and reduced lead time.	Demonstrated the relevance of Lean practices for SMEs.	Did not examine Machine Learning integration.
Yuphin & Ruanchoengchum (2020)	Lean and Machine Learning Case Study	Sprocket manufacturing company	Production efficiency increased by 74%, while turnaround time decreased by 10%.	Provided strong evidence of Lean–ML synergy in manufacturing operations.	Limited to a single production environment.
Weichert et al. (2019)	Industry 4.0 Literature Review	Manufacturing organizations	Machine Learning improved predictive maintenance, quality prediction, and production planning.	Established the theoretical foundation for ML-driven manufacturing optimization.	Did not specifically address SME implementation.
Kaiser et al. (2023)	Industrial AI Study	Manufacturing systems	Machine Learning enabled real-time, data-driven decision-making.	Clarified the role of predictive analytics in digital manufacturing.	Limited discussion on waste reduction mechanisms.
Hassan et al. (2013)	Lean Manufacturing Analysis	Manufacturing industry	Lean Manufacturing effectively reduced process waste and improved workflow efficiency.	Provided evidence supporting Lean as a waste-reduction methodology.	Did not incorporate digital technologies or predictive analytics.
Grewal et al. (2008)	Process Improvement Study	Industrial operations	Lean implementation improved flow efficiency and operational productivity.	Established foundational concepts of Lean-based process optimization.	Conducted before the emergence of Industry 4.0 technologies.

Thematic Analysis Results

The thematic analysis revealed that waste identification and reduction was the most frequently discussed theme across the reviewed studies. Lean Manufacturing literature consistently emphasized the importance of eliminating non-value-added activities through practices such as Just-in-Time (JIT), Value Stream Mapping (VSM), Kaizen, Kanban, and Standardized Work. Hassan et al. (2013) reported that systematic lean implementation contributes significantly to production waste reduction through continuous identification of inefficiencies and process improvement. Likewise, Grewal et al. (2008) demonstrated that Value Stream Mapping enables organizations to visualize process bottlenecks and identify opportunities for operational improvement.

The second dominant theme concerned the application of Machine Learning for predictive analytics and decision support. Unlike Lean Manufacturing, which relies heavily on observation and historical process evaluation, Machine Learning enables organizations to process large volumes of operational data and generate predictive insights. Weichert et al. (2019) found that Machine Learning improves production planning accuracy through predictive analysis and real-time monitoring, while Kaiser et al. (2023) emphasized that recent advances in cloud-based analytics and low-cost AI solutions have increased accessibility for SMEs.

The third theme focused on production process optimization. Studies consistently reported that Machine Learning techniques such as classification, regression, clustering, and anomaly detection improve process visibility and facilitate early identification of production inefficiencies. Nevertheless, most studies examined these technologies independently of Lean Manufacturing practices, leaving significant gaps in understanding how predictive analytics can systematically support continuous improvement initiatives.

Synthesis of Lean Manufacturing and Machine Learning Integration

The review findings suggest that Lean Manufacturing and Machine Learning operate through complementary mechanisms. Lean Manufacturing provides a structured framework for identifying and eliminating waste, whereas Machine Learning enhances predictive capability through data-driven analysis. Consequently, Machine Learning strengthens Lean Manufacturing practices by enabling proactive rather than reactive decision-making.

Table 2. Integration Mechanisms between Lean Manufacturing and Machine Learning

Waste Category	Lean Manufacturing Practice	Machine Learning Function	Expected Outcome
Overproduction	Just-in-Time (JIT)	Demand forecasting	Reduced excess production
Waiting Time	Value Stream Mapping (VSM)	Bottleneck prediction	Reduced idle time
Defects	Quality Control and Kaizen	Defect classification	Improved product quality
Unnecessary Motion	Standardized Work	Motion pattern analysis	Improved labor productivity
Excess Inventory	Kanban	Inventory forecasting	Optimized inventory levels

The findings indicate that Machine Learning does not replace Lean Manufacturing; rather, it extends its capabilities. While Lean tools identify waste after it becomes observable, Machine Learning enables organizations to anticipate potential waste events before they occur.

From Reactive to Predictive Improvement

One of the most significant findings emerging from the review is the transition from reactive improvement to predictive improvement. Traditional Lean Manufacturing approaches generally identify inefficiencies after waste has already occurred.

In contrast, Machine Learning continuously analyzes production variables including production time, equipment utilization, defect rates, inventory levels, and demand fluctuations to predict future inefficiencies. The review suggests that the integration mechanism follows three sequential stages: (1) Data acquisition from production activities; (2) Predictive analysis using Machine Learning algorithms; (3) Preventive intervention through Lean Manufacturing practices.

This mechanism explains how production systems can evolve from corrective actions toward preventive and predictive management strategies.

Challenges and Opportunities for SMEs

Despite its potential benefits, the review identified several recurring barriers, including limited digital infrastructure, poor data quality, insufficient analytical expertise, and organizational resistance to change. Jia and Puvanasvaran (2020) emphasized that SMEs often struggle to sustain Lean initiatives because of resource constraints and technological limitations.

Nevertheless, substantial opportunities also exist. The increasing availability of cloud computing, Software-as-a-Service (SaaS) analytics platforms, and user-friendly Machine Learning tools has significantly reduced adoption barriers. According to Mittal et al. (2020), these technological developments are making smart manufacturing increasingly accessible to SMEs, creating favorable conditions for gradual Lean–Machine Learning integration.

Conceptual Implications

The review demonstrates that the integration of Lean Manufacturing and Machine Learning represents a complementary operational system rather than a simple combination of independent approaches. Lean Manufacturing provides the operational logic for waste elimination, while Machine Learning supplies predictive intelligence that enhances decision-making quality.

Unlike previous studies that examined Lean implementation or Machine Learning adoption separately, this study synthesizes evidence from fifteen selected studies to propose a conceptual integration framework tailored to SME environments. The framework explains how predictive analytics can strengthen traditional waste reduction practices, thereby enabling SMEs to improve operational efficiency, production quality, competitiveness, and digital transformation readiness.

Overall, the findings suggest that Lean Manufacturing and Machine Learning integration offers a promising conceptual pathway for transforming SME production systems from reactive operational management toward predictive and data-driven continuous improvement.

Conclusions

This study systematically reviewed the integration of Lean Manufacturing (LM) and Machine Learning (ML) for waste prediction and production process optimization in Small and Medium Enterprises (SMEs). Based on the analysis of fifteen selected studies, five key themes were identified: waste reduction, predictive analytics, production process optimization, implementation barriers, and digital transformation readiness. The findings indicate that Lean Manufacturing and Machine Learning have complementary characteristics, where Lean Manufacturing provides a framework for waste elimination, while Machine Learning enhances predictive and data-driven decision-making capabilities.

The literature synthesis suggests that integrating these approaches may support the transition from reactive waste management to more predictive and proactive production management. Several reviewed studies reported improvements in production efficiency, quality control, process monitoring, and waste prediction. However, the reported outcomes vary depending on organizational characteristics, technological readiness, and implementation conditions, particularly within SME environments.

This study does not provide direct empirical validation of Lean–ML integration. Instead, it proposes a conceptual framework that explains how Machine Learning can strengthen Lean Manufacturing practices in SMEs. The framework contributes to the operations management and digital manufacturing literature by identifying key integration mechanisms, barriers, and enabling factors.

Future research should focus on empirically validating the proposed framework through case studies, surveys, or longitudinal investigations in SMEs. Further studies are also needed to evaluate different Machine Learning algorithms and develop practical implementation models that accommodate the resource constraints commonly faced by SMEs.

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