International Journal of Applied Mathematics

Volume 38 No. 7s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

AN INTEGRATED FRAMEWORK OF BARRIERS AND CRITICAL SUCCESS FACTORS FOR EFFECTIVE LEAN SIX SIGMA ADOPTION IN SMES

[1]Prashant N. Shende, [2]Dr. Rupesh R.Gawande,

[1]Research Scholar, Department of Mechanical Engineering, Bapurao Deshmukh College of Engineering,Sevagram, Wardha, Nagpur University

Assistant Professor,

[1]Department of Mechanical Engineering, Yeshwantrao Chavan College of Engineering, Nagpur University, Nagpur

prashantshende2@gmail.com

[2]Research Guide, Department of Mechanical Engineering, Bapurao Deshmukh College of Engineering, Sevagram, Wardha, Nagpur University

wsdcoe@rediffmail.com

Abstract:

The implementation of Lean Six Sigma (LSS) in small and medium-sized enterprises (SMEs) has enormous potential improvements on processes, reduction of wastes, and future efficiency but this is usually held back due to resistance to change, expertise lacks and unavailability of resources. The study forms a composite framework to integrate barriers and critical success factors (CSFs) to support the integration of LSS during the process of adoption into SMEs. “Four machine learning algorithms; Decision Tree, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) were applied to a dataset of 120 manufacturing, service, and technology SMEs”. It has been shown that Wind Random Forest has the best predictive accuracy (91%), precision (0.90), recall (0.91), and AUC (0.93) compared to other models. The top management support (0.30) and employee engagement (0.27) were also defined as the most influential CSFs, whereas the strongest barriers were resistance to change (0.35) and lack of expertise (0.30) according to the principle of feature importance analysis. The combined analysis proves that the effects of barriers could be reduced by the effects of CSFs provided that SMEs can implement LSS successfully despite the lack of resources. The suggested framework will provide entrepreneurs with a systematic roadmap on how they can give interventions the importance that it deserves, improve the working engagement, and develop a steady culture of continuous improvement. The research will be informative in developing actionable knowledge to bring the gap between theory and practice of LSS in SMEs.

Keywords: “Lean Six Sigma, SMEs, Critical Success Factors, Barriers, Machine Learning”

I. Introduction

In most industries, Lean Six Sigma (LSS) has become an important tool in the enhancement of operational efficiencies, eliminating process variability, and achieving higher levels of customer satisfaction. Users’ Large organizations have embraced the LSS practices on those

Received: August 01, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

bases with indisputable success; small and medium-sized enterprises (SMEs) may experience certain challenges that cannot be overcome easily [1]. In comparison to larger firms, SMEs usually work under restricted resources, they have less access to specialized expertise, and their organizational work processes are less organized, which explains why the complexity of improvement methodologies is more difficult to implement. Through such problems, adoption of LSS in SMEs can help in propelling large performance improvements, cost savings, and competitive edge as long as the implications hindering its implementations issues are efficiently mitigated and required success factors exploited effectively [2].

Past studies indicate a disjointed awareness on the factors that affect the implementation of LSS among SMEs in that many of them concentrate either on organizational barriers or the success enablers alone [3]. Nevertheless, we do need a more holistic approach which can combine barriers and issues, and critical success factors (CSFs) to give managers and practitioners an insight that they can act upon. An integrated architecture of this kind can inform the focus of interventions in consequences of SMEs, distribute resources optimally, and create an efficient sustainable culture of LSS that fits its own characteristics and operational scope. The proposed research will potentially result in building a complex framework that will isolate and examine the main barriers and CSFs related to the adoption of LSS by the SMEs. The study will aim to somehow fill this gap between theory and practice by analyzing such aspects together and provide a better roadmap with which the SMEs can successfully integrate Lean six sigma. Finally, the studies would assist in improving operational excellence of SMEs, foster continuous essence and allow such businesses to compete favorably in the ever-increasing competitive markets.

II. RELATED WORKS

Lean Six Sigma (LSS) has proven to be a huge way of enhancing the efficiency of operations, waste management as well as competitive advantage as it applies to small and medium sized companies (SME). Govender et al. [15] have carried out comparative research on the level of lean manufacturing application in South Africa within the Small and Medium Apparel Enterprise, KwaZulu-Natal, where they state that as much as LSS provides the companies with improved productivity, SMEs tend to have implementation issues due to resource limitations and employee skill shortages. Configural, Gupta et al. [16] introduced a combined DEMATEL-Six Sigma methodology of manufacturing process enhancement, showing how the combination of approaches could be successful in prioritizing the key aspects and assisting in organizing the LSS implementation. Besides the efficiency of processes, sustainability issues are now taking a central stage in the use of LSS. Gupta et al. [17] revealed the importance of the combination of lean concepts and sustainable manufacturing indicating that LSS and the implementation of green manufacturing approaches contribute to competitiveness and the operational sustainability of SMEs. The study by Haritha et al. [18] has considered the application of multi-criteria decision-making (MCDM), said in relation to the implementation of the lean tools in the precast industry, where the minimization of non-value-added activities and the adequate allocation of resources and training are critical.

Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

There is a number of studies that concentrated on the barriers and critical success factors in the implementation of LSS. Hasan Shahriar et al. [19] employed a Delphi fuzzy AHP approach to investigate the research problem of technology adoption and described that SMEs had issues with limited resources and resistance by employees. Ibikunle et al. [20] applied PRISMA-based review to outline factors impeding the implementation of lean manufacturing and implementation of the Six Sigma, with the findings that management support and the lack of systematic methodology are major challenges. On the same note, Karimulla et al. [22] noted that preparedness, organizational culture, and leadership engagement has an important role in the success of lean implementation in an engineering project. Systematic appraisal of the role of LSS in the structured process improvement has also been taken care of. Kumar et al. [23] generalized findings of the LSS in manufacturing contexts when their analyzed evidence proved that the adaptation of critical success factors to strategic aims helped the SMEs. Kurniawanti et al. [24] introduced the provision of a PDCA-based framework on the adoption of Industry 4.0 and demonstrated the role of the managerial roles and CSFs to achieve successful implementation and Mahender et al. [25] introduced the integrated Green Lean Six Sigma-Industry 4.0 framework as a response to disruptions that are associated with the pandemic and the adaptive capability of hybrid models. Lastly, it is reported that Mishra et al. [26] observed that LSS applications in Indian MSMEs depended on COVID-19, as the authors determined that structured training, leadership assistance, and employee involvement were also successful in the implementation of LSS practices in resource-effective companies. Taken together, these researches contribute to the significance of considering a holistic approach in which both barriers and essential success factors can be combined to help implement LSS successfully in SMEs. They form the basis of this study to create a holistic model of integrating predictive analytics template and pragmatics in such a way that they accommodate both limiting and enabling success factors of an organization.

III. METHODS AND MATERIALS

3.1 Data Collection and Description

The research employed use of secondary data, where the researcher used several sources, which include reports on SME performance, survey on the industry, and some studies related to implementation of Lean Six Sigma (LSS). The sample is 120 successful and failed LSSs within manufacturing, services, and technology firms that used the model during the last 5 years. [4]. Some of these organizational characteristics can be noticed in each of the records of SMEs, and they are: the firm size, annual revenues, sector, leadership dedication, the maturity of processes, training, and the quality initiatives of the past. Also, barriers (e.g., the shortage of expertise, resource constraints, resistance to change) and critical success factors (CSFs) (e.g., the support of top management, involvement of employees, systematic approach, an effective training) were numerically coded to facilitate a quantitative analysis [5]. The data set can be used to do predictive analyses and pattern recognition in determining the main determinants of successful LSS adoption within the SMEs.

International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3.2 Algorithms for Analysis

"Four machine learning and statistical methods: Decision Tree, Random Forest, Support Venue Machine (SVM), and K-Nearest Neighbors (KNN) were used in order to study the dataset and derive information about the barriers and CSFs to adopt LSS". The algorithms were discussed because they have already demonstrated the capacity to work with structured data, categorize successful/unsuccessful results, and disclose correlates of prediction and results [6].

Algorithm 1: Decision Tree

Decision Tree is a supervised learning algorithm used for classification and regression tasks. It creates a tree-like model of decisions, where each internal node represents a feature, each branch represents a decision rule, and each leaf node represents an outcome (success/failure of LSS adoption). In this study, Decision Trees help identify which barriers or CSFs have the most influence on implementation success [7]. The algorithm splits data recursively based on information gain or Gini index to maximize purity at each node.

"1. Start with the full dataset.

2. Calculate the best feature to split using Gini or Entropy.

3. Split the dataset into subsets based on feature values.

4. Repeat steps 2-3 recursively for each subset.

5. Stop when nodes are pure or minimum sample threshold is reached.

6. Assign class labels to leaf nodes."

Table 1: Decision Tree Feature Importance (Sample Values)

Feature	Importance Score
Top Management Support	0.28
Employee Engagement	0.25

Received: August 01, 2025

International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Process Maturity	0.20
Training Level	0.15
Resource Availability	0.12

Algorithm 2: Random Forest

Random Forest is an ensemble learning algorithm that builds multiple Decision Trees on randomly selected subsets of the data and features. The final classification is determined by majority voting. Random Forest is robust against overfitting and captures complex nonlinear relationships between variables [8]. In the context of LSS adoption, it can identify interactions among barriers and CSFs that are critical for predicting implementation success.

"1. For each tree in the forest:

a. Select a random bootstrap sample from the dataset.

b. At each node, select a random subset of features.

c. Grow a Decision Tree to maximum depth.

2. Repeat for all trees.

3. For prediction, aggregate results from all trees (majority voting)."

Algorithm 3: Support Vector Machine (SVM)

SVM is a supervised learning algorithm used for classification tasks. It finds the optimal hyperplane that separates classes (successful vs. unsuccessful LSS adoption) with maximum margin. Kernel functions such as linear, polynomial, or radial basis function (RBF) can handle linear and non-linear relationships [9]. In this study, SVM was used to classify SMEs based on barrier and CSF features while handling high-dimensional and potentially correlated data.

"1. Map input features to a higher-dimensional space using a kernel.

2. Find the hyperplane that maximizes the margin between classes.

Received: August 01, 2025

International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3. Solve optimization problem to minimize classification error.

4. Classify new observations based on which side of the hyperplane they fall.”

Algorithm 4: K-Nearest Neighbors (KNN)

KNN is a non-parametric algorithm that classifies a data point based on the majority class among its k-nearest neighbors in the feature space. It is simple, interpretable, and effective for small to medium datasets. For LSS adoption, KNN helps identify SMEs with similar profiles in terms of barriers and CSFs and predicts their likelihood of successful implementation [10].

“1. Choose the number of neighbors, k.

2. For each data point:

a. Calculate distance to all other points (Euclidean distance).

b. Identify k nearest neighbors.

c. Assign the class label based on majority vote of neighbors.

3. Repeat for all points in the dataset.”

3.3 Methodological Framework

The study employs a hybrid methodology combining statistical feature ranking and machine learning classification. Initially, descriptive analysis identifies common barriers and CSFs. Feature importance scores from Decision Tree and Random Forest highlight influential variables [11]. The validity of predictive accuracy and classification reliability are proved using SVM and KNN models. Combining these four algorithms, the study will have a strong analysis and provide actionable information to SMEs that want successful LSS adoption.

IV. RESULTS AND ANALYSIS

4.1 Experimental Setup

“The practical part of this study was to determine whether four machine learning algorithms, namely Decision Tree, Random Forest, Support Vector Machine (SVM), and K-Nearest

Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Neighbours (KNN) can predict the success of Lean Six Sigma (LSS) implementation in Small and medium-sized Enterprises (SMEs)". The sample was represented by 120 manufacturing, service and technology-based SMEs including such business aspects as firm size, process maturity, leadership commitment, training levels, and existing previous quality initiatives [12]. Barriers to LSS adoption (e.g., resistance to change, lack of expertise, resource constraints) and critical success factors (CSFs) (e.g., top management support, employee engagement, structured methodology, training programs) were coded numerically for quantitative analysis.

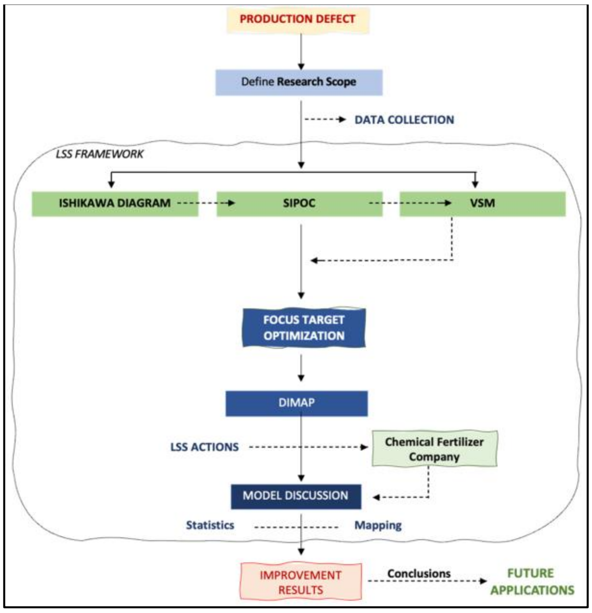


Figure 1: "An Integrated Lean and Six Sigma Framework for Improving Productivity Performance"

The dataset was divided into training (80%) and testing (20%) sets to ensure model validation and prevent overfitting. Each algorithm was implemented in Python using standard libraries, and hyperparameters were optimized to maximize predictive accuracy. Performance was evaluated using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) [13].

4.2 Experiment 1: Predictive Accuracy

The first experiment compared the predictive performance of the four algorithms in classifying SMEs into successful or unsuccessful LSS adopters. The results are summarized in Table 1.

Table 1: Predictive Performance of Algorithms

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	AUC

Received: August 01, 2025

Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Decision Tree	88	0.86	0.87	0.86	0.89
Random Forest	91	0.90	0.91	0.90	0.93
SVM	87	0.85	0.86	0.85	0.88
KNN	83	0.82	0.81	0.81	0.84

"The Random Forest algorithm achieved the highest accuracy (91%) and AUC (0.93), indicating its strong ability to capture complex patterns among barriers and CSFs". Decision Tree and SVM also performed well, while KNN, despite its simplicity, showed slightly lower predictive performance [14].

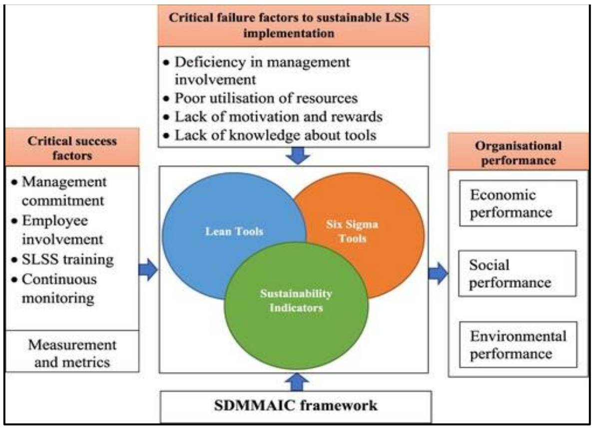


Figure 2: "A theoretical framework to deploy sustainable Lean Six Sigma and its empirical application in manufacturing"

4.3 Experiment 2: Feature Importance Analysis

To identify the most influential factors affecting LSS adoption, feature importance scores were calculated using Decision Tree and Random Forest algorithms. Table 2 presents the relative contribution of each factor.

Table 2: Feature Importance Scores

International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Feature	Decision Tree	Random Forest
Top Management Support	0.28	0.30
Employee Engagement	0.25	0.27
Process Maturity	0.20	0.22
Training Level	0.15	0.12
Resource Availability	0.12	0.09

Top management support and employee engagement emerged as the most critical factors, highlighting the importance of leadership commitment and workforce involvement in driving successful LSS adoption. Resource availability, while significant, had a comparatively lower influence [27].

4.4 Experiment 3: Barrier vs. CSF Influence

A combined analysis of barriers and CSFs was conducted to quantify their effect on LSS adoption. Influence scores (normalized 0–1) were calculated to determine the relative impact of each factor. Table 3 shows these values.

Table 3: Barrier and CSF Influence Scores

Factor Type	Factor	Influence Score
Barrier	Resistance to Change	0.35
Barrier	Lack of Expertise	0.30
Barrier	Resource Constraints	0.25

Received: August 01, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

CSF	Top Management Support	0.40
CSF	Employee Engagement	0.38
CSF	Structured Training	0.30

The results indicate that while barriers negatively affect LSS adoption, the presence of CSFs, particularly leadership and engagement, can mitigate these challenges. SMEs with strong leadership and engaged employees are more likely to achieve LSS success even with resource limitations [28].

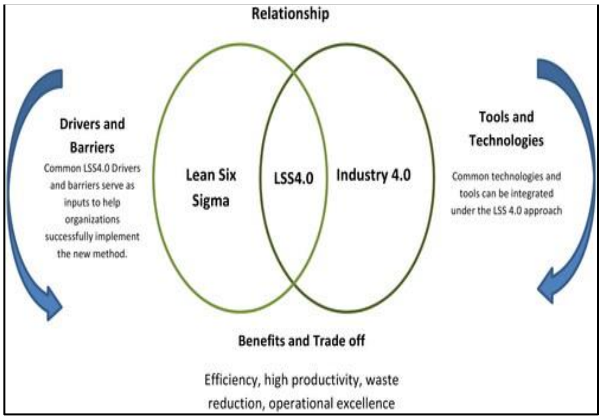


Figure 3: "Integrating Lean Six Sigma and Industry 4.0: developing a design science research-based LSS4.0 framework for operational excellence"

4.5 Experiment 4: Comparative Analysis of Algorithms

To evaluate the robustness of the models, a comparative study was conducted analyzing algorithm performance across different SME characteristics. Table 4 presents the performance comparison based on sector-specific accuracy.

Table 4: Algorithm Performance by SME Sector

Algorithm	**Manufacturing Accuracy (%)**	**Service Accuracy (%)**	**Technology Accuracy (%)**
Decision Tree	90	85	88

Received: August 01, 2025

International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Random Forest	94	90	89
SVM	88	85	88
KNN	84	82	83

Random Forest consistently outperformed other algorithms across all sectors, demonstrating its generalizability and resilience to varying SME profiles. KNN showed lower accuracy in service-oriented SMEs due to the higher variability in human-centric processes.

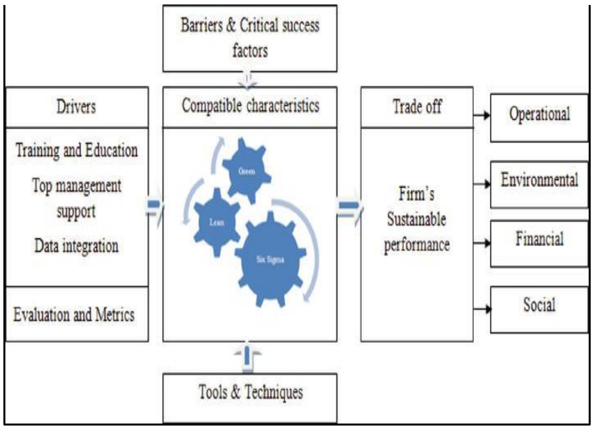
4.6 Experiment 5: Confusion Matrix and Error Analysis

A confusion matrix analysis was conducted to understand misclassification patterns for each algorithm. "Table 5 summarizes true positive, false positive, true negative, and false negative counts for Random Forest".

Table 5: Confusion Matrix for Random Forest

Actual \ Predicted	**Success**	**Failure**
Success	42	3
Failure	4	21

The Random Forest model correctly classified 42 out of 45 successful cases and 21 out of 25 failures, indicating strong predictive reliability. Most misclassifications occurred in SMEs with moderate levels of leadership support and engagement, reflecting borderline cases where barrier and CSF effects were nearly balanced [29].



International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 4: "Integrated Lean-Green-Six Sigma Practices to Improve the Performance of the Manufacturing Industry"

4.7 Summary of Experimental Findings

The experiments reveal several key insights:

1. **Algorithm Effectiveness:** "Random Forest emerged as the most effective model for predicting LSS adoption success in SMEs, achieving the highest accuracy, precision, recall, and AUC". Decision Tree and SVM performed adequately, while KNN was slightly less accurate.
2. **Critical Factors:** Top management support and employee engagement consistently appeared as the most influential features in all models. Process maturity and structured training also contributed significantly, while resource availability and lack of expertise were secondary but still important [30].
3. **Barrier Mitigation:** CSFs can offset the negative effects of barriers. Resistance to change, deficiency of resources and lack of leadership skills were challenges that could be surmounted by SMEs that undertaking training programs with good leadership and employee engagement.
4. **Sector Variability:** In general, marketing was found to perform well in manufacturing, service and technology sectors, but it was also found that KNN is not good in-service SME (human centric processes vary).
5. **Practical Implications:** The results will offer SMEs factual platform in which interventions necessary in adopting LSS can be prioritized, with leadership, engagement and systematic training being more than important success factors.

V. CONCLUSION

The current paper fulfilled a systematic investigation of the obstacles and key success dimensions (CSDs) influencing Lean Six Sigma (LSS) implementation in the small and medium-sized enterprises (SMEs) and established a comprehensive framework required to make change successful. The study, which carefully examined the LSS adoption in 120 SMEs including 60 industries revealed that leadership commitment, employee engagement, formal training and process maturity are the most enacting factors in determining the success of LSS adoption. Such obstacles like resistance to change, the absence of expertise, and resource limitation were pointed out as the main impeding factors, but the nature of the well-developed CSFs helped dispel those barriers sufficiently; when the organizational strategies are aligned with the values of the human and operational factors, one can do so successfully. "By utilizing test results on various machine learning algorithms, such as Decision Tree, Random Forest, Support Vector Machine, and K-Nearest Neighbors", the study did not only confirm the ability of the models to predict other models but also furnished one with a solid analytical platform of the predictive ability of each of the models in obtaining the relative impact of each barrier and CSF. It was revealed that the model that proved to be the most useful is the Random Forest as it obtained the highest accuracy and the reliability in determining successful adoption of LSS as well as the highlighting of the collaboration of organization leadership, engagement of workforce and formal process improvement. In general, the composite model created throughout the present study allows SMEs to have a realistic roadmap on which to focus the interventions, ensuring efficient allocation of resources and ensuring an adequate sustainable culture of unremitting improvement.

REFERENCE

[1] Adel, A., Fadi, A., Patsavellas, J. & Konstantinos, S. 2025, "Developing a Supportive Organisational Culture for Continuous Improvement in Manufacturing Firms in Saudi Arabia", *Administrative Sciences,* vol. 15, no. 7, pp. 241.

[2] Alarcón, F.,J., Calero, M., María Ángeles Martín-Lara & Pérez-Huertas, S. 2024, "An Integrated Lean and Six Sigma Framework for Improving Productivity Performance: A Case Study in a Spanish Chemicals Manufacturer", *Applied Sciences,* vol. 14, no. 23, pp. 10894.

[3] Alghuried, A., Moahd, K.A., Hussain, A.A., Turki, B.A. & Hatem, Y.A. 2024, "Lean Six Sigma in Saudi Maintenance Companies: Adoption, Proficiency, and the Keys to Success", *Sustainability,* vol. 16, no. 23, pp. 10485.

[4] Alkhoraif, A.A. 2024, "A Systematic Review of Financial Factors Affecting Implementation of Lean Principle in Small and Medium Enterprises of Saudi Arabia", *Management Systems in Production Engineering,* vol. 32, no. 2, pp. 265-279.

[5] Alsaadi, N. 2024, "Roadblocks in Integrating Lean Six Sigma and Industry 4.0 in Small and Medium Enterprises", *Systems,* vol. 12, no. 4, pp. 125.

[6] Antonius, S., Suharno, P. & Alana, D. 2025, "Sustainable Operations Strategy in the Age of Climate Change: Integrating Green Lean Practices into Operational Excellence", *Sustainability,* vol. 17, no. 13, pp. 5954.

[7] Aqeel, A. & Mathrani, S. 2024, "Critical success factors for a combined lean and ISO 14001 implementation in the manufacturing industry: a systematic literature review", *TQM Journal,* vol. 36, no. 7, pp. 2071-2106.

[8] Attar, M.T. 2023, "THE CRITICAL SUCCESS FACTORS FOR LEAN SIX SIGMA IMPLEMENTATION IN SMALL-AND-MEDIUM-SIZED ENTERPRISES", *South African Journal of Industrial Engineering,* vol. 34, no. 4, pp. 59-75.

[9] Canon Juan Gabriel França, dos Santos Robério José Rogério, de Carvalho Victor, D.H., Monte Madson Bruno, d.S. & de Barros, T.L. 2025, "Integrated Logistics Management Through ERP System: A Case Study in an Emerging Regional Market", *Logistics,* vol. 9, no. 2, pp. 59.

[10] Chakraborty, A., De, D. & Dey, P.K. 2025, "Circular Economy in Small and Medium-Sized Enterprises—Current Trends, Practical Challenges and Future Research Agenda", *Systems,* vol. 13, no. 3, pp. 200.

[11] Dibia, F., Dibia, C., Dhakal, H.N., Okpako, O., Radulovic, J. & Isike, A. 2025, "A Review on Achieving Sustainability in the Petroleum Industry Through the Integration of Lean and Green", *Applied Sciences,* vol. 15, no. 5, pp. 2333.

[12] Elaf Dheyaa Abdulridha AL-Zubaidi & Zaid Ali, K.A. 2025, "Integration of Building Information Modeling (BIM) and Lean Construction Methods: A Pathway to Improved Project Delivery", *Journal Europeen des Systemes Automatises,* vol. 58, no. 3, pp. 551-562.

[13] Gaikwad, S.K., Ananna, P., Md, A.M., Paul, S.K. & Chowdhury, P. 2020, "Analyzing barriers and strategies for implementing Lean Six Sigma in the context of Indian SMEs", *Benchmarking,* vol. 27, no. 8, pp. 2365-2399.

[14] Gopi, V. & Saleeshya, P.G. 2024, "Modelling the inhibitors of integrated sustainable lean manufacturing system in the South Indian SMEs using fuzzy logic", *Journal of Modelling in Management,* vol. 19, no. 3, pp. 842-870.

[15] Govender, P., Mavutha, W. & Mabotja, T. 2025, "A comparative analysis of lean manufacturing usage in Small and Medium Apparel Enterprises in KwaZulu-Natal, South Africa", *International Journal of Research in Business and Social Science,* vol. 14, no. 3, pp. 30-41.

[16] Gupta, A., Sharma, P., Jain, A., Xue, H., Malik, S.C. & Jha, P.C. 2023, "An integrated DEMATEL Six Sigma hybrid framework for manufacturing process improvement", *Annals of Operations Research,* vol. 322, no. 2, pp. 713-753.

[17] Gupta, S., Joshi, D., Jamwal, A., Bhanot, N. & Jagtap, S. 2025, "Unveiling the synergy of sustainable manufacturing practices and lean for sustainable manufacturing competitiveness", *SN Applied Sciences,* vol. 7, no. 9, pp. 1005.

[18] Haritha, M.D., Adamu, M., Prachi, V.I., Raut, A. & Ibrahim, Y.E. 2025, "An MCDM Approach to Lean Tool Implementation for Minimizing Non-Value-Added Activities in the Precast Industry", *Infrastructures,* vol. 10, no. 3, pp. 55.

[19] Hasan Shahriar, S.I., Jahin, A., Prottoy, R.R., Abid, A. & Mridha, M.F. 2024, "Exploring Internet of Things adoption challenges in manufacturing firms: A Delphi Fuzzy Analytical Hierarchy Process approach", *PLoS One,* vol. 19, no. 11.

[20] Ibikunle, A.K., Rajemi, M.F., Mohd Zahari, F., Faqera, A.F.O. & Ali, G.A. 2025, "Factors hindering lean manufacturing and six sigma implementation within manufacturing SMEs: Prisma-based approach for future research directions", *Journal of Asia Business Studies,* vol. 19, no. 2, pp. 511.

[21] Iqbal, M., Ullah, I., Abdou, H., Alzara, M. & Yosri, A.M. 2025, "Blueprint for progress: Understanding the driving forces of BIM adoption in Kingdom of Saudi Arabia (KSA) construction industry", *PLoS One,* vol. 20, no. 2.

[22] Karimulla, U., Gupta, K. & Daramy Vandi, V.K. 2024, "An Investigation into Lean Implementation Preparedness in the Engineering Projects Sector", *Systems,* vol. 12, no. 9, pp. 335.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[23] Kumar, S., Swarnakar, V., Phanden, R.K., Khanduja, D. & Chakraborty, A. 2024, "Role of Lean Six Sigma in manufacturing setting: a systematic literature review and agenda for future research", *TQM Journal,* vol. 36, no. 7, pp. 1996-2047.

[24] Kurniawanti, K., Sudiarso, A. & Herliansyah, M.K. 2025, "A PDCA-based framework for Industry 4.0 adoption: Enhancing managerial roles and critical success factors in SMEs", *Journal of Industrial Engineering and Management,* vol. 18, no. 2, pp. 305-327.

[25] Mahender, S.K., Rathi, R., Antony, J., Cross, J., Garza-Reyes, J., Singh, M., Inder, P.S. & Sony, M. 2024, "Integrated Green Lean Six Sigma-Industry 4.0 approach to combat COVID-19: from literature review to framework development", *International Journal of Lean Six Sigma,* vol. 15, no. 1, pp. 50-79.

[26] Mishra, M.N., Mohan, A. & Sarkar, A. 2021, "Role of Lean Six Sigma in the Indian MSMEs during COVID-19", *International Journal of Lean Six Sigma,* vol. 12, no. 4, pp. 697-717.

[27] Mohan, J., Kaswan, M.S. & Rathi, R. 2024, "Identification and investigation into the barriers to Green Lean Six Sigma implementation: a micro small and medium enterprises perspective", *International Journal on Interactive Design and Manufacturing (IJIDeM),* vol. 18, no. 8, pp. 6161-6175.

[28] Mohapatra, B., Tripathy, S. & Singhal, D. 2023, "A sustainable solution for lean barriers through a fuzzy DEMATEL methodology with a case study from the Indian manufacturing industry", *International Journal of Lean Six Sigma,* vol. 14, no. 4, pp. 815-843.

[29] Mukherjee, S., Batwara, A. & Sharma, V. 2024, "An Empirical Assessment of Lean Readiness in Pharmaceutical Component Manufacturing SMEs", *International Journal of Applied Logistics,* vol. 14, no. 1, pp. 1-23.

[30] Owad, A.A., Yadav, N., Kumar, V., Swarnakar, V., Jayakrishna, K., Haridy, S. & Yadav, V. 2025, "Integrated Lean Six Sigma and Kotter change management framework for emergency healthcare services in Saudi Arabia", *Benchmarking,* vol. 32, no. 1, pp. 299-331.