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Lean Six Sigma and Business Analytics Integration: A Systematic Literature Review

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ABSTRACT

Aims :
This study aims to present a novel and comprehensive mapping of the integration between Lean Six Sigma (LSS) and Business Analytics (BA) through a systematic review of publications from 2020 to 2025, and to develop a conceptual LSS–BA framework based on four analytical layers.

Design/Methodology/Approach :
This study employed a PRISMA-guided Systematic Literature Review with a two-stage approach: 20 Q1–Q2 journal articles were analyzed to map general Lean Six Sigma trends, while 10 selected articles were examined in depth to identify Business Analytics integration and data-driven practices.

Findings :
The review reveals that LSS implementation remains highly dependent on traditional DMAIC tools and methods, while the use of advanced analytical approaches such as machine learning, predictive analytics, and text mining is still limited, particularly in the Analyze and Control phases. Digital integration appears only in a small proportion of the reviewed studies

Research Limitations/Implications :
The main limitations include the lack of detailed quantitative evidence in existing publications and the uneven adoption of BA practices across LSS studies. These findings imply the need for stronger empirical validation and broader digital transformation in continuous improvement initiatives.

Originality / Value :
This study offers original value by providing a structured synthesis of recent LSS–BA research and proposing a four-layer conceptual framework that can guide future development of data-driven and prescriptive process improvement systems.

Introduction

Lean Six Sigma (LSS) is a combination of two approaches, namely Lean and Six Sigma, which have been widely used in various industries and proven effective in improving company operational performance [1]. Lean itself is a management concept introduced by the Toyota Production System (TPS) in the 20th century, with a focus on eliminating waste that does not provide added value, and improving the overall process flow of a system [2]. Meanwhile, Six Sigma itself is a statistical-based approach first developed by Motorola in 1980, with the main goal of eliminating or reducing defects and variances that occur in a production process [3]. This was further popularized by General Electric under the leadership of Jack Welch in the 1990s. Although both approaches have different focuses, with Lean on speed and efficiency, and Six Sigma on quality and consistency, with the limitations of both supporting innovation by integrating both into LSS, Lean without Six Sigma often results in a fast but unstable process, while Six Sigma without Lean can result in a highly controlled but less efficient process [4]. Therefore, LSS comes as a holistic approach that combines the advantages of both through a structured framework such as DMAIC (Define, Measure, Analyze, Improve, Control) [5].

With current business competition, particularly in the modern industrial era characterized by uncertain demand and increasing demands for efficiency and quality, organizations are required to develop process management approaches capable of sustainably improving performance [6]. One approach that has proven effective in addressing these challenges is LSS, an integrated methodology that combines the waste-reduction principles of Lean with the process-variation control of Six Sigma. This integration focuses not only on operational efficiency but also on systematically improving quality and customer satisfaction [7].

As its development progresses, the LSS approach is no longer limited to the manufacturing sector but has expanded to various sectors such as healthcare, logistics, education, and the public sector [8]. This demonstrates the flexibility and adaptability of LSS in improving process performance across various organizational contexts. The authors' analysis of LSS research in the 2020–2025 period shows a growing trend towards improving process performance, reducing variation, and strengthening operational capabilities across sectors, particularly manufacturing, healthcare, and logistics. It appears that LSS studies during this period are still dominated by classical methodologies such as DMAIC, DMADV, and several variations that are being developed on a limited basis. These approaches remain the primary framework for process improvement because they are considered systematic, structured, and relatively easy to adapt to various organizational contexts.

Despite the increasing number of publications, the general focus of LSS research remains on improving operational performance indicators such as productivity, quality, overall equipment effectiveness (OEE), lead time, and reducing defect rates, without significant changes to the methodological paradigm [9]. This suggests that the LSS research landscape until 2025 will remain conventional, with an emphasis on optimizing existing processes. In other words, while LSS's contribution to operational performance improvement is quite consistent, the approaches used do not fully reflect the shift toward a more data-driven system for advanced business analytics (BA).

Business Analytics (BA) is a set of methods and technologies used to process data into meaningful information through four levels of analysis: descriptive analytics (understanding what happened), diagnostic analytics (explaining why something happened), predictive analytics (predicting what might happen), and prescriptive analytics (recommending optimal actions) [10],[11]. The BA function is crucial in an organization because it can improve the quality of data-driven decision-making more comprehensively, making it not only reactive but also proactive and strategic [12]. Meanwhile, in the context of LSS, which fundamentally upholds the principle of data-driven improvement, BA integration should strengthen every stage of process improvement, especially by more accurately identifying root causes, modeling improvement scenarios, and making optimal decisions based on predictions. However, to date, LSS research tends to stop at conventional statistical analysis tools and has not demonstrated the systematic use of BA within its methodological framework. This condition indicates a significant conceptual gap, in which the potential for integrating LSS and BA as a modern analytical approach has not been explored in depth in previous research.

Literature Review

LSS is widely recognized as an integrated process improvement methodology that combines the waste-reduction orientation of Lean with the variation-reduction capability of Six Sigma [13], [14]. Lean focuses on eliminating non-value-added activities and improving process flow, while Six Sigma emphasizes defect reduction, process stability, and statistical control [15]. The integration of these two approaches provides a structured mechanism for improving operational performance, particularly through the DMAIC cycle: Define, Measure, Analyze, Improve, and Control. DMAIC enables organizations to identify process problems, measure performance gaps, analyze root causes, implement improvement actions, and maintain process control [16]. For this reason, DMAIC remains the dominant framework in LSS research and practice across manufacturing, healthcare, logistics, services, and other organizational contexts [17], [18].

Business Analytics (BA) refers to the use of analytical methods, technologies, and data-processing capabilities to transform organizational data into meaningful and actionable knowledge [12], [19]. In general, BA is classified into four analytical levels: descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Descriptive analytics explains what has happened, diagnostic analytics identifies why it happened, predictive analytics estimates what may happen in the future, and prescriptive analytics recommends what actions should be taken. In process improvement contexts, these analytical levels support organizations in moving beyond reactive decision-making toward more evidence-based, predictive, and optimized improvement actions [20].

The emergence of Industry 4.0 and global digital transformation has changed the nature of operational data in modern organizations. Production systems, enterprise platforms, customer interfaces, sensor-based technologies, and supply chain networks increasingly generate large volumes of real-time, heterogeneous, and complex data [21]. This development creates both opportunities and challenges for traditional LSS implementation. Although conventional LSS tools such as Value Stream Mapping, Fishbone Diagram, Root Cause Analysis, Failure Mode and Effects Analysis, and control charts remain useful for structured problem solving, they may be insufficient to address complex data environments that require rapid analysis, predictive modeling, and continuous monitoring [22], [23]. Therefore, integrating BA into LSS is increasingly important for strengthening the analytical capacity of process improvement initiatives.

Conceptually, LSS and BA share a common foundation in data-driven decision-making. LSS offers a structured improvement logic through DMAIC, while BA provides analytical capabilities to describe, diagnose, predict, and prescribe improvement actions based on data. In the Define and Measure phases, BA can support problem identification, customer requirement analysis, and real-time performance measurement. In the Analyze phase, predictive analytics and machine learning can strengthen root cause analysis by identifying patterns that may not be captured by conventional tools. In the Improve and Control phases, simulation, optimization, anomaly detection, and prescriptive analytics can support better decision-making and sustainable process control. This conceptual relationship provides the theoretical basis for integrating LSS and BA as a more adaptive, data-driven, and analytically robust process improvement framework.

Research Methods

Protocol and Registration

This study employed a Systematic Literature Review (SLR) approach guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The PRISMA framework was used to ensure transparency, consistency, and replicability in identifying, screening, selecting, and analyzing relevant studies. Although this review was not formally registered in an external review database, the review protocol was developed internally by defining the research objective, search strategy, inclusion and exclusion criteria, data extraction variables, and synthesis procedures prior to article selection.

Searching Strategy and Data Source

The literature search was conducted to identify high-quality scientific publications related to Lean Six Sigma research during the 2020–2025 period. The search focused on articles published in reputable international journals ranked Q1 or Q2 by the Scimago Journal Rank (SJR). Several academic databases were used as primary data sources, including Scopus, ScienceDirect, Wiley Online Library, Taylor S Francis Online, SpringerLink, and Emerald Insight. These databases were selected because they provide broad access to peer-reviewed journal articles in quality management, operations management, industrial engineering, and business analytics.

The keywords used in the search process were formulated to capture the most current spectrum of LSS research and to identify integration opportunities with Business Analytics. The combination of keywords included: ‘Lean Six Sigma’, ‘DMAIC’, ‘DMADV’, ‘process improvement’, ‘continuous improvement’, ‘operational excellence’, ‘Lean tools’, ‘Six Sigma tools’, ‘manufacturing performance’, and ‘quality improvement’. To broaden the scope, additional terms related to data-driven contexts were also applied, such as ‘analytics’, data-driven decision-making’, and ‘digital transformation in LSS’. However, initial findings indicate that the number of articles directly linking BA and LSS remains very limited. All keywords were applied using Boolean operators (AND, OR, and wildcard (*) to ensure maximum inclusion of articles relevant to the research framework.

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were established to ensure that the selected articles were relevant to the research objectives and met the required academic quality. Articles were included if they met the following criteria: published between 2020 and 2025, written in English, published in Q1 or Q2 peer-reviewed journals, available in full-text format, and explicitly discussed Lean Six Sigma or its methodological variants such as DMAIC, DMADV, or related process improvement frameworks. Articles were also considered relevant if they addressed LSS implementation in manufacturing, healthcare, logistics, services, SMEs, or other organizational contexts.

Articles were excluded if they were conference papers, book chapters, editorials, short communications, extended abstracts, technical reports, or non-peer-reviewed publications. Studies that did not explicitly discuss Lean Six Sigma, DMAIC, or related LSS methodologies were also excluded. In addition, articles without full-text access or those that did not provide sufficient methodological information for analysis were removed from the final selection. Based on the PRISMA screening process, 20 eligible Q1–Q2 journal articles were retained for general mapping of Lean Six Sigma research trends, while 10 selected articles were further analyzed in depth because they explicitly contained indicators related to Business Analytics integration, digital technology adoption, predictive analysis, or data-driven decision-making.

Inclusion and Exclusion Criteria

The study selection process followed the PRISMA flow. In the identification stage, 104 articles were initially identified using the selected keywords and database searches. During the screening stage, duplicate and irrelevant records were removed, and 64 articles were considered relevant based on title and abstract screening. In the eligibility stage, 20 articles were assessed through full-text review. After applying the document type, journal ranking, language, publication year, and full-text availability criteria, 20 articles were categorized as eligible studies for mapping general Lean Six Sigma research trends. From these eligible studies, 10 articles were selected for in-depth analysis because they specifically addressed Business Analytics indicators, digital integration, predictive analysis, or data-driven decision-making in Lean Six Sigma practices. This two-stage selection approach allowed the study to distinguish between general LSS research trends and focused LSS–BA integration patterns.

Inclusion and Exclusion Criteria

Data extraction was conducted using a structured review matrix to ensure consistency across the selected studies. The extracted data included author names, publication year, article title, journal name, research method, industrial sector, LSS methodology used, LSS tools applied, performance indicators, and evidence of Business Analytics or data-driven practices. For the focused subset of 10 articles, additional coding was conducted to identify the presence of descriptive, diagnostic, predictive, and prescriptive analytics within the DMAIC phases.

The synthesis process combined descriptive and conceptual analysis. Descriptive synthesis was used to map publication trends, sectoral distribution, methodological patterns, and the frequency of LSS tools across the selected articles. Conceptual synthesis was used to examine how Business Analytics could be integrated into the DMAIC structure. The findings were then used to develop an LSS–BA conceptual framework that links each DMAIC phase to four levels of analytics: descriptive, diagnostic, predictive, and prescriptive. This approach enabled the study to identify both the dominant patterns in recent LSS research and the emerging opportunities for data-driven and analytics-based process improvement.

PRISMA Method

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram was used to ensure that the Systematic Literature Review (SLR) process was conducted transparently and systematically. The study selection process began with 104 articles identified through a Scopus search using the keywords "Lean Six Sigma" and "case study" for the publication period 2020–2026. After the initial screening, 64 articles were deemed relevant based on their titles and abstracts. Of these, 20 articles were further evaluated through full-text assessment. Applying the document criteria, including English-language journal articles, article type, final publication version, and Q1–Q2 journal ranking, resulted in 20 eligible articles for mapping general Lean Six Sigma research trends. From these 20 eligible articles, 10 articles were selected for in-depth analysis because they specifically addressed Lean Six Sigma applications with Business Analytics indicators, digital technology adoption, predictive analysis, or data-driven decision-making. These 10 articles were then incorporated as the primary studies for the focused LSS–BA integration analysis. Details are presented in Figure 1, which illustrates the PRISMA flow diagram used in this study.

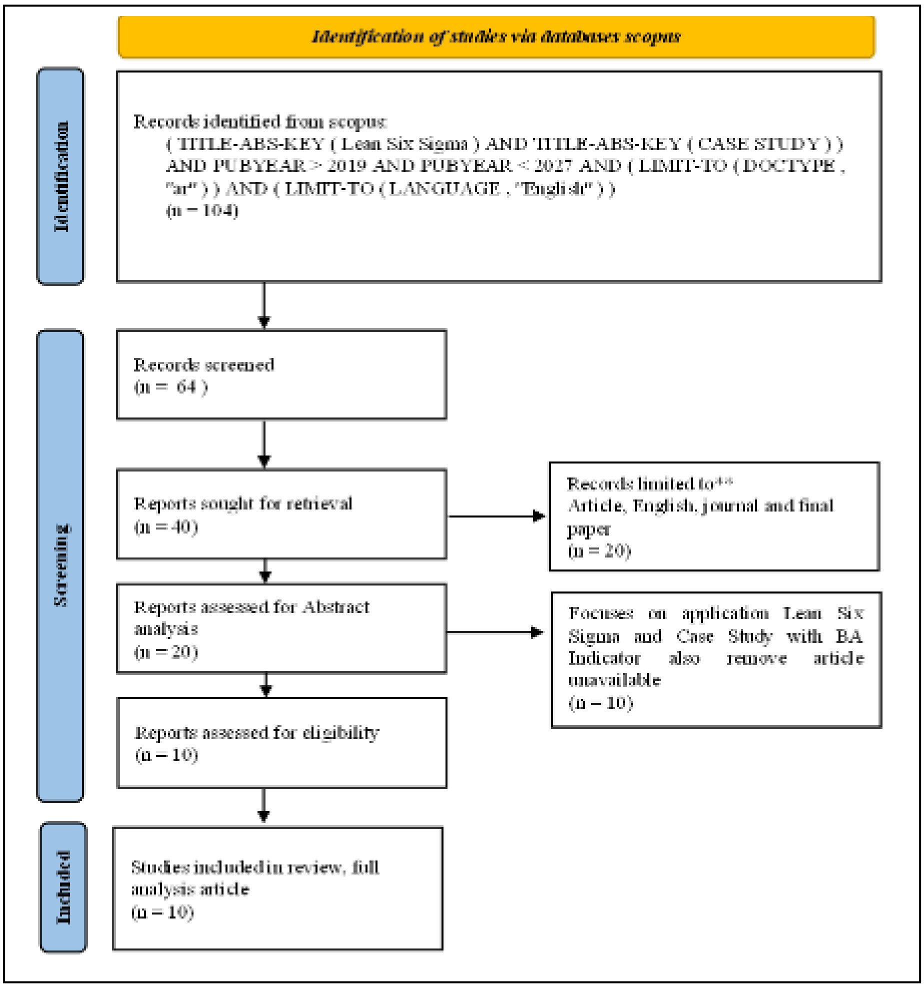

Figure 1. PRISMA Diagram
(Source : Data Processing)

Result and Discussion

1) Result

Descriptive Analytics of LSS Research (2020–2025)

The selected studies suggest an ongoing evolution of Lean Six Sigma (LSS) from conventional process improvement toward more technology-enabled and data-driven practices. Publication activity increased notably during the COVID-19 pandemic, when many organizations began implementing DMAIC to stabilize processes and mitigate operational uncertainty [24]. This trend continued through 2024, with an increasing number of studies exploring process digitalization and the integration of LSS with technology-based systems, as reflected in, who highlighted the integration of digital tools within the Lean Six Sigma framework. Overall, the publication pattern indicates that LSS remains a relevant and adaptable approach to shifts in the global business environment [25].

From a sectoral distribution perspective, the majority of studies were from the manufacturing and healthcare sectors, two sectors that have historically adopted LSS most extensively for quality enhancement and process efficiency. Studies such as those by demonstrate that LSS has become an essential approach for improving healthcare service performance, particularly through case-based improvement. [26]. Meanwhile, other research has focused on the application of LSS in the manufacturing industry, such as [27], who emphasized defect reduction through the DMAIC approach. The service, logistics, and small and medium sized enterprises (SME) sectors also featured in a moderate number of studies, indicating growing interest in improving process efficiency, although their contribution remains smaller than those of the two major sectors.

Methodologically, the analysis shows that DMAIC accounts for approximately 80–85% of the publications analyzed. This dominance is consistent with the perception of DMAIC as the most applicable methodology for solving operational problems across sectors [27]. Meanwhile, other methods, such as DMADV, DMEDI, and hybrid variants, appear only in limited numbers, typically associated with redesign or process-innovation projects [28]. Several recent studies have begun integrating DMAIC with digital approaches such as machine learning, simulation, and analytics-driven decision support [29], indicating a methodological evolution of LSS toward more data-driven systems.

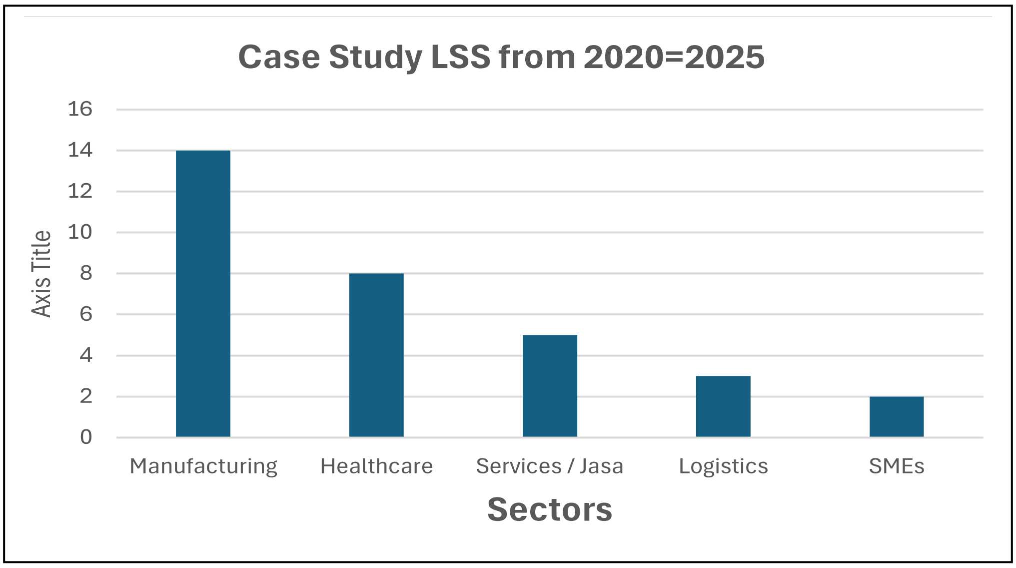

Figure 2. LSS Case study from 2020-2025
(Source : Data Processing)

Figure 2 illustrates the sectoral distribution across the 20 eligible Lean Six Sigma studies analyzed in this review. The manufacturing sector dominates the reviewed studies, accounting for 45% of the total studies, reflecting its historical position as the primary

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adopter of LSS methodologies. The healthcare sector follows with a 25% contribution, driven mainly by the increasing need for efficiency improvement and patient safety during the 2020–2025 period. The service and logistics sectors contribute 15% and 10%, respectively, indicating that LSS adoption is beginning to expand into non-manufacturing and operational service environments. Meanwhile, the SME sector accounts for only 5%, suggesting that the application of LSS in small and medium-sized enterprises remains limited, possibly due to resource constraints and insufficient technical capability to implement more structured process improvement methodologies. Overall, this pattern demonstrates that while LSS remains strong within traditional industries, the potential for expansion into other sectors remains wide open

Overview of Included Studies

The included studies demonstrate that Lean Six Sigma research remains strongly centered on DMAIC implementation while gradually expanding toward digital and analytics-supported process improvement practices. This pattern suggests increasing opportunities for integrating Business Analytics within the LSS framework. These studies were published in several high-impact journals, including Production Planning and Control, International Journal of Lean Six Sigma, The TQM Journal, and the International Journal of Quality and Reliability Management, reflecting ongoing academic interest in LSS as a relevant approach to operational efficiency. In addition, recent publications show a growing trend toward integrating technology and process digitalization, including the use of analytical tools and data-driven systems. [29]. Overall, this distribution illustrates the evolution of LSS toward more evidence-driven practices and greater readiness for integration with Business Analytics.

Table 1 summarizes the 20 Lean Six Sigma studies that form the basis of the analysis, including authors, publication year, article title, journal, LSS methodology applied, and industrial sector. This table helps map variations in methodologies, application contexts, and the strength of each study's contribution to the current Lean Six Sigma literature. By observing the distribution across journals and sectors, the table provides a comprehensive overview of how LSS has been utilized across various domains over the past five years, while also confirming the research trend toward digital and analytics-oriented integration.

Table 1. Summary of Lean Six Sigma Studies (2020–2025)

Authors (Year)	Title	Journal	Method	Sector
(Gupta et al., 2024)	Integrating TOC, Lean & Six Sigma with Digitalization Tools	Production Planning & Control	DMAIC	Manufacturing
(Buestan et al., 2024)	Lean Six Sigma for Health Care: Multi-Case Study	International Journal of Lean Six Sigma	DMAIC	Healthcare
(Praharsi et al., 2021)	Lean Six Sigma in the Era of COVID-19	International Journal of Lean Six Sigma	DMAIC	Services
(Araman & Saleh, 2023)	LSS Implementation in Aluminum Profiles Extrusion	The TQM Journal	DMAIC	Manufacturing
(Trakulsunti et al., 2022)	Reducing Medication Errors Using LSS	TQM & Business Excellence	DMAIC	Healthcare
(Şişman, 2023)	Implementing LSS to Reduce Defects	International Journal of Lean Six Sigma	DMAIC	Manufacturing
(Panayiotou et al., 2022)	Using LSS in SMEs	International Journal of QRM	DMAIC	SME
(Srijithesh et al., 2024)	Leveraging LSS in Industry 4.0	IJQRM	DMAIC	Manufacturing

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(Singh & Rathi, 2024)	Environmental Lean Six Sigma Implementation	The TQM Journal	DMAIC	Manufacturing
(Sonhaji et al., 2024)	IT-Based Lean Six Sigma Implementation in Indonesia	Cogent Business & Management	DMAIC	Services

(Source : Data Processing)

Distribution of LSS Tools across Studies

The analysis of the selected studies shows that recent Lean Six Sigma (LSS) implementations continue to be dominated by conventional improvement tools centered on process visualization, problem identification, and structured decision-making. Their high frequency of use indicates that most DMAIC applications still prioritize operational understanding and incremental improvement rather than analytical sophistication [29]. In contrast, statistical and computational approaches appear less frequently, suggesting that contemporary LSS practice remains largely dependent on descriptive and diagnostic capabilities rather than advanced analytical reasoning. This pattern reflects that methodological development in LSS has progressed more slowly than the broader movement toward digital and data-intensive process improvement.

Which presents the distribution of tools, provides a comprehensive overview of tool selection trends in LSS implementation over the past five years. The table shows that process-mapping tools such as VSM, RCA/5 Whys, and Fishbone Diagrams are used most frequently due to their ease of application across sectors and high effectiveness during the Define and Analyze stages. Tools such as FMEA and PDCA appear with moderate frequency, reflecting their relevance in risk management and continuous improvement. Conversely, the relatively lower use of statistical tools indicates that many LSS projects during this period are oriented toward qualitative operational improvements and do not require complex statistical modeling. Therefore, the table not only illustrates tool selection patterns but also highlights the broader research direction of LSS, which continues to emphasize problem identification and root cause analysis rather than predictive or prescriptive model development.

Table 2. Distribution of Lean Six Sigma Tools Across 20 Studies (2020–2025)

No	LSS Tool	Frequency
1	Value Stream Mapping (VSM)	21
2	Root Cause Analysis (RCA / 5 Why)	18
3	Fishbone / Ishikawa Diagram	16
4	Failure Mode and Effects Analysis (FMEA)	14
5	SPC / Control Charts	10
6	PDCA Cycle	11
7	Others (SIPOC, Pareto, Checksheet, etc.)	0

(Source : Data Processing)

Mapping Research Gaps Toward Business Analytics

The reviewed literature indicates that contemporary LSS research remains strongly oriented toward conventional improvement logic, while the integration of Business Analytics (BA) is still relatively underdeveloped. Existing implementations largely rely on historical observations, manual interpretation, and qualitative diagnosis, which limits their ability to generate predictive or prescriptive insights. This limitation becomes particularly visible in the Analyze and Control phases, where advanced analytical capabilities should ideally support pattern recognition, forecasting, and adaptive decision-making. Furthermore, only a limited number of studies connect performance measurements to computational models that enable proactive process management. This gap highlights an important opportunity to reposition DMAIC from a retrospective improvement framework to a more intelligent, analytics-driven system. Future development may focus on integrating IoT infrastructures, cloud-based analytics environments, and machine-learning–assisted decision mechanisms to strengthen process responsiveness, analytical accuracy, and long-term operational sustainability.

Figure 3 illustrates the potential integration of Business Analytics within each DMAIC phase, with varying degrees of opportunity intensity. The Measure and Analyze phases present the strongest opportunities for applying diagnostic and predictive analytics, as both require deeper data processing and pattern extraction to identify root causes. Meanwhile, the Improve and Control phases provide space for prescriptive analytics through simulation, optimization, and algorithmically driven automated monitoring systems. This heatmap reinforces that although DMAIC is traditionally procedural, each phase offers real opportunities to be strengthened through Business Analytics, enabling faster, more accurate, and data-driven decision-making.

Table 3. Heatmap BA Opportunities Across DMAIC

DMAIC Phase	*Business Analytics (Probability)*			
	Descriptive	Diagnostic	Predictive	Prescriptive
Define	Low	Low	Low	Low
Measure	High	Medium	Low	Low
Analyze	High	High	sedang	Low
Improve	Medium	Medium	Medium	sedang
Control	Medium	Medium	Medium	High

(Source : Data Processing)

2. Discussion

The publication trend for Lean Six Sigma (LSS) from 2020 to 2025 shows a substantial increase in research interest, particularly after the COVID-19 pandemic, when organizations began focusing on improving process efficiency and operational resilience. The rise in publications between 2021 and 2023 indicates that LSS remains relevant as a foundational process-improvement approach across both the manufacturing and service sectors [24]. After 2023, several studies began shifting their focus from purely traditional LSS approaches to integrating digital technology and data analytics, as reflected in emerging themes such as digitally enabled LSS and Industry 4.0 LSS. This confirms that the evolution of LSS lies not only in methodological development but also in its integration with modern data-driven decision-support systems.

Among the 20 studies analyzed, DMAIC dominates approximately 84% of research methodologies, demonstrating that this classic problem-solving structure remains the primary standard for LSS implementation in industrial practice. The dominance of DMAIC implies that LSS research still relies heavily on manual diagnostic approaches, such as RCA, Fishbone, and FMEA, which tend to yield tactical, short-term solutions Sisman, 2023 [30]. While these methods are effective for root-cause identification, a key limitation is the minimal adoption of advanced analytics capable of handling complex data, modeling process variability predictively, or providing automated prescriptive recommendations. In other words, the current use of DMAIC remains largely 'paper-based' and has not yet been fully optimized with business analytics.

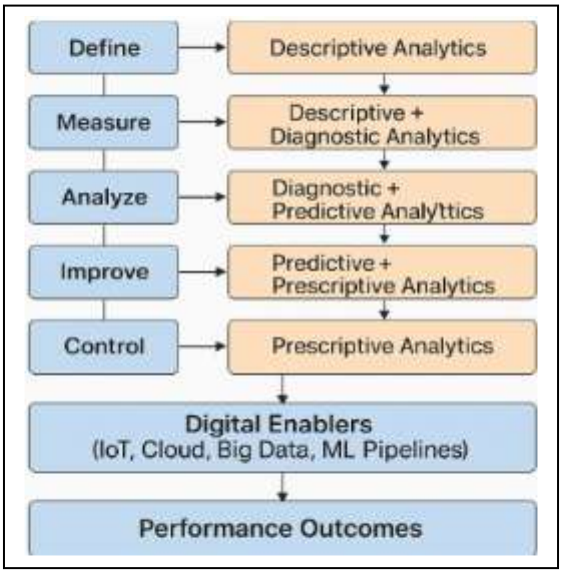

Figure 3. LSS–BA Integration Framework
(Source : Data Processing)

The research gap analysis indicates that each phase of DMAIC presents clear opportunities for integration with Business Analytics. The Define phase can be enhanced through text mining for VOC; Measure through sensor-based data, IoT, and automated measurement; Analyze through machine learning for root-cause prediction; Improve through simulation optimization; and Control through statistical learning and anomaly detection [29]. This combination demonstrates that LSS–BA integration not only increases decision-making speed and accuracy but also supports real-time, data-driven continuous improvement. Therefore, it is recommended to develop an integrative LSS–BA model that aligns the analytical pipeline (descriptive, diagnostic, predictive, prescriptive) with each DMAIC phase, creating a more innovative, adaptive, and scalable process-improvement approach.

Figure 3 illustrates the conceptual framework for integrating Lean Six Sigma with Business Analytics by mapping the DMAIC phases to the four levels of analytics: descriptive, diagnostic, predictive, and prescriptive. The model shows that the early DMAIC phases are better suited to descriptive and diagnostic analytics, while the Analyze, Improve, and Control phases offer greater potential for predictive and prescriptive analytics. This framework emphasizes that LSS–BA integration does not alter the structural integrity of DMAIC but rather enriches its analytical rigor and decision-making capability using digital technologies and data-driven insights.

Conclusion

This study concludes that Lean Six Sigma (LSS) remains the dominant approach for process improvement and quality control during the 2020–2025 period, with the DMAIC method being the most widely adopted framework across sectors such as manufacturing, services, and healthcare. Publication trends indicate a significant increase during the postpandemic period, when organizations sought to reinforce operational efficiency and process resilience. Correspondingly, recent studies demonstrate a shift in research focus toward integrating digital technologies and Industry 4.0, particularly through digitally enabled LSS and the use of big data for data-driven decision-making.

Despite this development, most of the reviewed studies still emphasize traditional diagnostic tools such as Value Stream Mapping (VSM), Root Cause Analysis (RCA), and Failure Mode and Effect Analysis (FMEA). At the same time, the application of advanced analytics including machine learning, predictive analytics, simulation, and prescriptive modeling remains limited. This reflects insufficient optimization of modern LSS practices to address increasing process complexity, which requires real-time, data-intensive analysis, resulting in predominantly reactive, short-term improvement solutions.

The primary contribution (*novelty*) of this research lies in the development of an integrative Lean Six Sigma–Business Analytics (LSS–BA) framework that systematically maps opportunities for analytical integration within each phase of DMAIC. This framework provides practical conceptual guidance for researchers and practitioners to develop a smarter, more adaptive, and scalable data-driven process improvement system. The findings emphasize the need to transform LSS methodologies from manual diagnostic approaches toward a comprehensive analytical pipeline that incorporates descriptive, diagnostic, predictive, and prescriptive analytics.

Future studies are recommended to develop empirical LSS–BA models using real-time data, test predictive algorithms in the Analyze and Control phases, and explore digital technologies such as digital twins, IoT, cloud analytics, and automated anomaly detection to strengthen process sustainability and control precision. Therefore, future research directions are expected to bridge the gap between traditional LSS practices and the needs of modern industry, requiring faster, more accurate, and data-driven decision-making.

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