



AI in Lean Six Sigma: A Review of Industrial Implementations, Benefits, and Barriers

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Abstract

The present review addresses the concept of Artificial Intelligence (AI) integration in the methods of Lean Six Sigma (LSS), its industrial applications, advantages, and obstacles. The AI technologies like machine learning, predictive analytics, and computer vision can support LSS by facilitating real-time processing of data, forecasting decision-making, and optimization of processes. The paper presents the examples of successful applications in manufacturing, healthcare, services and logistics showing that the efficiency, quality and innovation are strongly improved. Nevertheless, the problems of data quality, cultural resistance, and lack of skills remain. The review concludes that AI-based LSS promotes smart and flexible and sustainable continuous improvement in line with Industry 4.0 and beyond.

Key words

Artificial Intelligence, Lean Six Sigma, Process Optimization, Predictive Analytics, Industry 4.0, Continuous Improvement.

Introduction

In the modern day competitive industrial environment, organizations are always trying to find methods to make things more efficient, eliminate wastage and to increase quality. The concept of Lean Six Sigma (LSS) has long been viewed as an effective means of accomplishing these goals as it combines the principles of waste minimization of Lean with the problem-solving paradigm of Six Sigma, which utilizes data to achieve its goals [1]. In the last 20 years, LSS has developed to



be a strategic management practice which is no longer limited in manufacturing but is currently extensively applied by health care, finance, logistics and service industries. Nevertheless, the more complex data environment encountered by industries, the more traditional LSS tools find it difficult to process the quantity, speed and diversity of data that is produced by the contemporary operations [2]. This dilemma has presented new possibilities of technological add-on using Artificial Intelligence (AI).

Machine learning (ML) and deep learning, natural language processing (NLP), and computer vision make up Artificial Intelligence and provide novel data analysis, prediction, and automation possibilities. With a combination of AI and LSS, organizations are able to attain intelligent process improvement, in which data collection, analysis and decision making is not only more rapid but also more precise and responsive [3]. The AI-based analytics are capable of detecting latent trends in process data, forecasting possible failures, refining parameters in real-time, and delivering useful insights that are beyond the human analytical features. This marriage between AI and LSS is a paradigm shift to a new brand of Smart Lean Six Sigma, which is in line with the overall trend of Industry 4.0 and the new vision of Industry 5.0, where human knowledge and intelligent systems work side by side [4].

There is more than a technological improvement to the introduction of AI into Lean Six Sigma: It is a strategic change. It holds significant gains including enhanced availability of the processes, real-time performance checking, predictive the structure of maintenance, and enhanced problem-solving. However, implementation of AI in the LSS framework has significant challenges to organizations that include technical constraints, data quality concerns, as well as cultural, high cost and skilled personnel. It is important to know the opportunities and challenges of such integration to enable practitioners and researchers to capitalize on the potential of AI in continued improvement programs [5].

So, this review will examine in detail the existing scenario of AI applications in Lean Six Sigma in industries. It summarizes the current literature to find the crucial areas of implementation, advantages, and obstacles and provides a systematic insight into the role of AI in making LSS

more effective. Critical success factors, research gaps, and future directions are also identified in the paper and will lead the development of AI-empowered process improvement systems [6].

Leaning Six Sigma and Artificial Intelligence Overview

Lean Six Sigma (LSS) is a guided and factual technique which integrates the effectiveness ideals of Lean production with the statistical rigor of Six Sigma. Lean aims at removing waste, streamlining process flow, and maximizing value as viewed by the customer whereas the Six Sigma aims at reducing variation, minimizing defects, and attaining consistent quality using the DMAIC (Define–Measure–Analyze–Improve–Control) cycle [7]. Lean and Six Sigma are a potent combination of continuous progress, business excellence, and strategic decision-making. Overtime LSS has been integrated into various sectors other than manufacturing like in the healthcare sector, logistics, information technology and service industries. Although it is a good tool, the traditional LSS tools have a high dependency on the past data, data analysis by human and interpretation, which may restrict its scalability and responsiveness to the big data and complex process systems of the age [8].

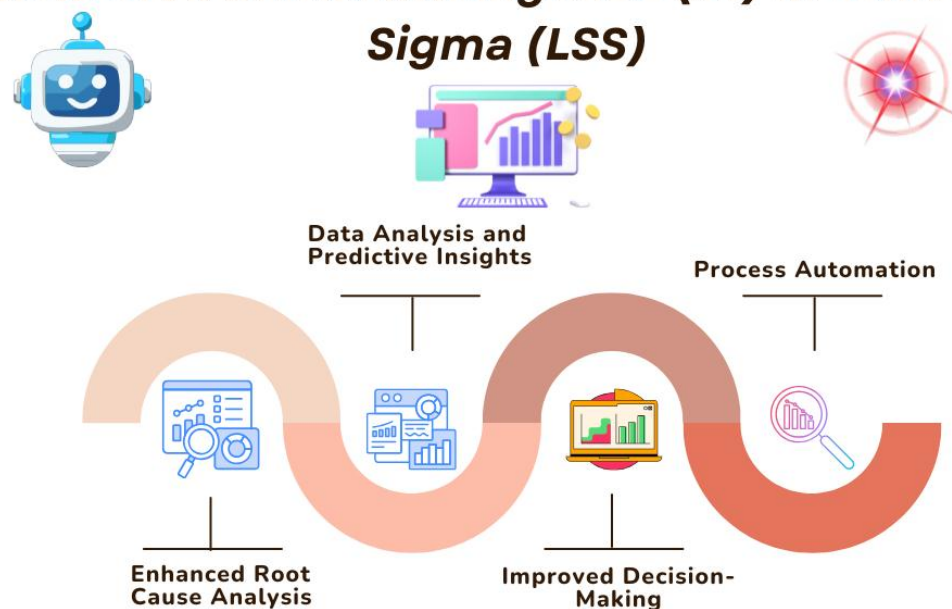


Figure: 1 showing benefits of integrating LSS with AI



Artificial Intelligence (AI), conversely, is a revolutionary collection of technologies that facilitate cognitive processing of machines, specifically, learning, reasoning, perception, and decision-making. The key AI fields that apply to LSS are machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and expert systems. Machine learning algorithms can study large datasets to uncover the underlying trends, forecast, and assist with making data-driven decisions, whereas NLP can process textual documentation of processes and customer reviews automatically [9]. Computer vision helps in real-time inspection and quality control, whereas, expert systems are used to recreate the logic used in decisions by humans to help in process improvement efforts. The capabilities of AI can be well aligned with the purposes of LSS as they will increase accuracy in the analytic process, minimize manual work, and facilitate proactive control over the processes [10].

AI and Lean Six Sigma are complementary, and thus, they are synergistic. LSS offers the systematized methodology and problem-solving field, whereas AI offers high-level analytical strength and automation. As an illustration, AI tools have the ability to gather and process sensor data, detect bottlenecks in the processes, and precisely determine the causes of the variation in the Measure phase and Analyze phase of the DMAIC [11]. Predictive models can also be used in the Improve and Control phases to propose the optimal process parameters and real-time performance monitoring. This combination of AI with LSS facilitates the creation of intelligent, dynamic, and self-optimizing systems which are necessary elements of the digital transformation initiative and Industry 4.0 system [12].

The past studies have already recognized the relevance of AI in improving the LSS outputs; nevertheless, official studies that summarize the applied applications, the advantage of the industry, and problems are scarce. The sections below of this review will attempt to fill this gap by looking at the implementation of AI-powered Lean Six Sigma practices within different industries, the practical benefits that have been realized, and the obstacles to larger implementation [13].



Methodology of the Review

In order to have a thorough and balanced perspective on how Artificial Intelligence (AI) has been applied to Lean Six Sigma (LSS) practices in industries, the systematic and structured research methodology is adopted in this review. The aim is to find, review, and generalize the existing literature that discusses the application, advantages, and obstacles of AI to the LSS framework. Having a transparent methodology does not only enhance the credibility of the review but also makes it possible to reproduce and have reliability of findings [14].

The study design and methodology encompassed a literature review and descriptive survey on the treatment of Ebola and its disease. The paper is based on a systematic literature review (SLR) methodology, which is informed by the Preferred Reporting Items of a Systematic Review and a Meta-analysis (PRISMA) model [15]. The review design involves a mixture of a qualitative and quantitative content analysis to be able to get the depth and breadth of the available research. It pays attention to peer-reviewed journal articles, conference papers, or credible industrial reports discussing the utilization of AI tools and techniques in the context of Lean Six Sigma or continuous improvement [16]. The key research questions that will guide the review are:

The search was done in several academic databases such as Scopus, Web of science, IEEE Xplore, ScienceDirect and Google Scholar. The keywords that were used together in the search string included: Artificial Intelligence, Machine Learning, Lean Six Sigma, Process Improvement, Industry 4.0 and Quality Management [17]. The keywords were combined with Boolean operators (AND, OR) and truncation symbols to guarantee an extensive search of the relevant publications. Only the publications of the last five years were included in the search since the concept of AI-powered digital transformation in the quality management area has emerged in recent years [18].

Only the studies which clearly explain the application of AI tools or techniques in the framework of LSS implementation were selected. Such papers that contain only traditional LSS without AI components, publications that were not in English, and those that could not be empirically or case-based were excluded. Both the qualitative case studies and quantitative analyses were taken into



account with enduring observations in order to end up with practical knowledge and quantifiable results [19].

The articles chosen were analyzed in a systematic manner regarding thematic coding. Industry sector, AI techniques, Lean Six Sigma tools included, perceived benefits, and perceived barriers were extracted. Qualitative synthesis was conducted to point out the emergent patterns and trends, and where appropriate descriptive statistics were implemented to summarize important results [20]. Such a methodological framework helps to make sure that not only academic positions are included in the review but also in the industry, which will give a considerate picture of how AI can be used to increase the effectiveness and sustainability of Lean Six Sigma in the contemporary industry [21].

AI in Lean Six Sigma Industrial Applications

The concept of Artificial Intelligence (AI) integration into Lean Six Sigma (LSS) has become a major wave in several industrial segments influencing the way organizations are going about to improve their processes and quality management. The use of AI technologies (machine learning, computer vision, natural language processing, and predictive analytics) is integrated into the conventional LSS systems to automatize the process of data collection, improve the root cause analysis and allow making real-time decisions [22]. This section presents critical industrial applications of AI in LSS in the manufacturing, healthcare, services, logistics, and other sectors explaining how digital intelligence is rebranding continuous improvement [23].

The most prolific arena of AI-enhanced Lean Six Sigma uses is still in the area of manufacturing. Firms are also using AI-based predictive analytics to optimize production factors, minimize machine downtime, and defects. Machine learning can be used in identifying variations in processes that add to waste and rework, and computer vision systems can also automate quality inspection compared to human assessors [24]. An example is predictive maintenance models, which enable the manufacturers to be able to know when equipment may fail even in advance—thus enhancing the effectiveness of the overall equipment (OEE) and minimizing unplanned

downtimes. These smart LSS systems have favored the automotive, electronics and aerospace industries making them to achieve greater efficiency, better yield and save on costs [25].

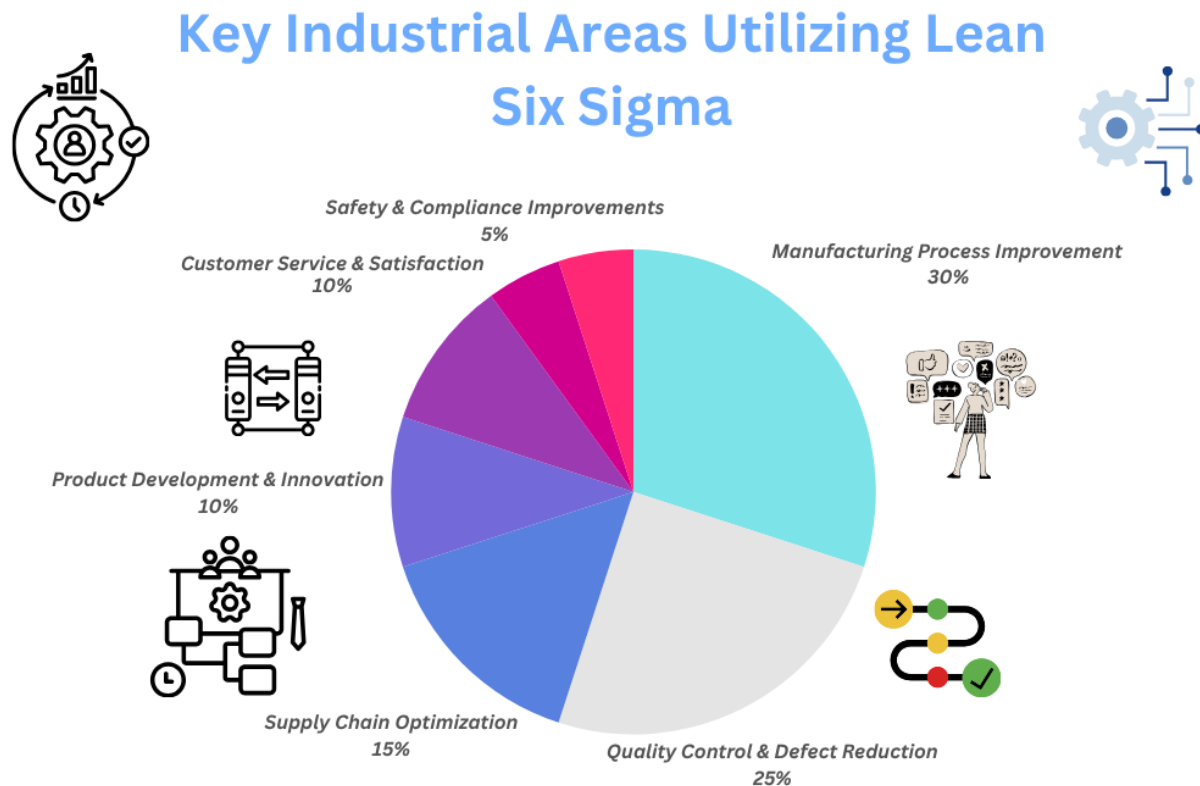


Figure: 2 showing key industrial areas utilizing lean six sigma

The use of AI in LSS systems in healthcare has shown impressive advances in patient care and resource use as well as operational efficiency. The patient flow, predictive treatment delays, and lessening medication mistakes have been studied using AI algorithms combined with the Six Sigma DMAIC process. The evidences have been facilitated by machine learning and data mining methods to assist with evidence-based decision-making by detecting process bottlenecks and optimizing patient scheduling [26]. In pharmaceutical production, AI models can guarantee a steady quality of the products, as they can identify the deviations of the essential parameters of the process, and Lean methods can optimize the production process and adherence to the regulations [27].

The banking, insurance, and telecommunications are service industries where AI-based LSS is becoming popular in order to improve the customer experience and operational efficiency.



Chatbots and NLP based systems are automated systems that handle routine customer service activities, predictive analytics are used to detect fraud, predict demand and resource allocation [28]. The lean principles assist in minimizing waste during service delivery processes, but the Six Sigma tools, enhanced with AI, would allow the accurate measurement of service quality and customer satisfaction. These applications indicate that LSS, in combination with AI, is capable of providing quantifiable returns even in knowledge-based and digital service settings [29].

When used together with Lean Six Sigma, AI, in logistics and supply chain management, improves visibility, accuracy in forecasting, and efficiency. The AI algorithms maximize the planning of routes, warehouse optimization, and inventory optimization, whereas Lean principles eradicate non-value-added operations. To illustrate, predictive demand modeling minimizes overstocking and stockouts, whereas real-time data analytics helps to improve the process continuously. The supply chains of companies that are already using AI-LSS report a high level of delivery reliability, lead time reduction, and better sustainability performance [30].

In every industry, effective implementations have similar best practices: effective leadership commitment, cross-functional cooperation, powerful data infrastructure, and unceasing skill development. The organizations that view AI as the facilitator of LSS methodologies and not its substitute are more successful. The results of the industrial case studies prove that AI-enabled Lean Six Sigma is one of the components of digital transformation that makes the operational excellence and the era of the intelligent automation compatible [31].

Benefits of AI Integration in Lean Six Sigma

The application of Artificial Intelligence (AI) to Lean Six Sigma (LSS) techniques has established an innovative level of operational excellence allowing organizations to shift towards reactive to problems to proactive and predictive decision-making. Although conventional LSS is susceptible to statistical software and human experience, AI complements them with the ability to process large volumes of information, identify complicated trends, and provide real-time solutions. The combination of AI and LSS has a wide range of practical and strategic advantages that enhance efficiency, quality, and innovation in industries [32].

Among the greatest advantages of AI integration, one can distinguish better process optimization and decision-making. Machine learning algorithms are used to analyze process data and identify the bottlenecks, inefficiencies, and variation sources that could not be observed with the help of traditional LSS tools [33]. Continuous learning on operational data is a feature of AI models, which enables the implementation of dynamic changes in the processes to enhance productivity and minimize waste. It also makes the process of decision-making faster and more accurate, because AI-assisted analytics provide data-driven recommendations in accordance with the principles of Lean of continuous improvement [34].

Benefits of integrating LSS with AI



Figure: 3 showing benefits of integrating LSS with AI

AI technologies provide an opportunity to gather and analyze data in real-time and change the approach to process improvement used by LSS practitioners. Before defects, equipment damages, or supply chain issues can arise, predictive analytics and deep learning models can predict these issues in advance [35]. This is a proactive strategy that enables organizations to take preventive measures and reduce downtime consequently ensuring a steady quality standard. As an example, predictive maintenance systems implemented in manufacturing using the Six Sigma control chart will give a warning on deviations in the process performance early, and thus minimizes the cost of rework and delays [36].



Quality control processes can also be greatly improved using AI which can detect the presence of anomalies and patterns in large volumes of data. In Image recognition and computer vision, such as the one discussed, have been able to detect defects on production lines much more accurately and consistently than when they were being inspected by hand [37]. These AI-based systems combined with the statistical rigor of Six Sigma guarantee the near-zero defect production. The end outcome is higher process capability (CPK), customer satisfaction and less waste, which are fundamental objectives of Lean methodology [38].

The systems with AI integration in LSS provide significant cost savings and efficiency benefits by automating the repetitive data analysis process and reducing the number of human errors. Lean practices remove non-value-added processes, whereas AI automatizes data-thusky processes, including measurement, reporting, and root cause analysis. This combination lowers the cycle time, decreases the time of project completion and optimizes the use of resources. Moreover, the organizations have recorded lower operational expenses and increased return on investment (ROI) as a result of better throughput and low variability [39].

The culture of data-based learning and the pursuit of continuous improvement created by AI is the perfect embodiment of the Lean Six Sigma philosophy. The AI systems reveal new ways of innovation and strategic enhancement to organizations with the help of clever analytics and pattern recognition. Also, AI helps in sharing knowledge and decision support enabling cross-functional teams to work together in a more effective way. This eventually results into smarter organizations with the ability to maintain long-term operational excellence [40]. The combination of AI enhances the advantages of Lean Six Sigma as the process improvement becomes more intelligent, agile, and data-based. It is not only the integrated strategy that enhances the performance in operations but also makes an organization more capable of adapting and being innovative in the dynamically evolving industrial environment [41].

Barriers and Challenges

Although the process of integrating Artificial Intelligence (AI) with Lean Six Sigma (LSS) has a significant potential in terms of optimizing the process and enhancing its quality, its application in



diverse industries does not lack challenges. Technical, organizational, financial, and ethical challenges are some of the most common problems encountered in organizations that disrupt the successful implementation of AI-based Lean Six Sigma models [42]. Practitioners and researchers need to understand these barriers in order to be able to develop effective strategies that can be used to make the most out of this integration and reduce the risks that may arise [43].

Among the most noticeable obstacles is the technical complexity of the AI systems and the quality of the information needed to operate it. AI models require large, clean, and structured data, which is frequently not applicable in practice in industrial settings. It can result in poor predictions and invalid information in case of incomplete, inconsistent, or noisy data. Further, the use of AI tools with the pre-existing Lean Six Sigma software or legacy systems has compatibility and interoperability problems [44]. Lots of organizations do not have the developed IT infrastructure, including cloud computing or Internet of Things (IoT) connections, to facilitate the large-scale AI applications in LSS projects.

The cultural resistance to change is among the biggest organizational obstacles to the adoption of AI-LSS. The management and employees might feel that AI threatens their positions or that it is a disruptive technology that breaks the customary methods of problem solving. Moreover, Lean Six Sigma used to be a people-based approach to problem resolution, which is based on teamwork and experience [45]. The automation introduced by AI can introduce a conflict between the human competencies and machine intelligence. In the absence of effective leadership, clear communication and employee involvement, companies are likely to have low levels of acceptance of AI programs within their Lean Six Sigma programs [46].



CHALLENGES OF INTEGRATING AI INTO LEAN SIX SIGMA



Figure: 4 showing challenges on integrating AI into lean six sigma

To use AI technologies as a part of LSS, it is necessary to spend a lot of money on the hardware, software, and data management systems as well as on training the workers. These costs could be prohibitive especially to small and medium-sized enterprises (SMEs). The payoff (ROI) of AI-LSSs project can also be delayed and cause uncertainty and reluctance to fund such projects. In addition, the lack of human resources that are capable of performing both AI and LSS tasks also hinders the scalability of integration and sustainability [47].

Immoral and legal issues are becoming severe because AI systems are capable of making decisions that can have a direct impact on operations and human efficiency. The lack of data privacy, prejudice of algorithms, and transparency can destroy the reliance on AI-led decision-making



processes. There are also substantial risks to the cybersecurity, particularly in the fields where AI tools analyze data of sensitive production or customers [48]. Realizing that data protection requirements and ethical considerations in AI applications are critical to responsible implementation are thus a key factor to be adhered to.

Discussion

The adoption of Artificial Intelligence (AI) as an element of the Lean Six Sigma (LSS) is a major change in organizational thinking on the issues of continuous improvement, optimization of processes, and decision-making. The above discussions have pointed out the transformative advantages as well as the exceptional challenges of this convergence. The findings are summarized in this discussion based on cross-industry application and critical factors of success, new trends, and the future role of human expertise in AI-powered Lean Six Sigma settings [49].

In all of its industries, including manufacturing, healthcare, services, logistics, finance, AI-based LSS has shown a steady ability to improve efficiency, accuracy, and innovation. Machine learning and computer vision systems have facilitated manufacturing industries to attain predictive maintenance and near perfection [50]. Data analytics that are supported by AI have been implemented in Six Sigma models to streamline patient flows and minimize medical errors in healthcare organizations. In the meantime, service and financial industries have used predictive and automation features of AI to enhance customer experience and agility of operations. Although this has been successful, adoption to a great extent differs across industries and may be based on the maturity of technology, data infrastructure, and organizational preparedness [51]. The industries that have a good digital ecosystem and data culture are likely to enjoy more of the benefits of AI-LSS integration.

The implementation of AI-LSS is a complex process that requires a number of factors to be successful. The principle of strong leadership commitment, strategic alignment, and innovation culture are the basis of resistance defeat and long-term sustainability. The quality of the data and their accessibility are also important; AI can be only as useful as the data it is using [52]. Also, the interdisciplinary teamwork of data scientists, LSS professionals, and business leaders also makes



the AI applications technically sound and aligned with the process improvement objectives. The process of continuous training and workforce development is also an essential factor to narrow the skills gap between the conventional process professionals and the future AI professionals [53].

Although AI provides analysis automation and fast decision-making, the human knowledge is still necessary to interpret results, change management and apply the contextual judgment. The triumph of the AI-LSS integration does not lie in substituting human beings, but in giving them smart tools, which increase their ability to solve problems [54]. Ethical decision-making, contextual flexibility and alignment with organizational values are also guaranteed by human control. With AI replacing daily analytical work, LSS professionals will be able to pay more attention to strategic planning, innovation, and leadership through continuous improvement [55].

The combs of case studies in different industries show that there are a couple of lessons to be learnt by the practitioners. Initial pilot projects that have quantifiable objectives are likely to gain momentum and confidence among the stakeholders. Incremental implementation Incremental implementation where the organization begins with processes that are data-rich and high-impact in nature will give the organization the opportunity to show tangible value before scaling [56]. Also, the implementation of AI into the known DMAIC (Define–Measure–Analyze–Improve–Control) model will increase its acceptance among users because it is not a replacement of Lean Six Sigma principles but an advancement of the principles. Lastly, it is necessary to continuously oversee and provide feedback to hone AI models and maintain process benefits in the long run [57].

Essentially, the discussion highlights that the integration of AI-LSS is not just a technological trend but an evolutionary technological shift towards intelligent, adaptive and people-centered continuous improvement. Those organizations that will be ahead of the age are those that will combine digital intelligence with human insight, that is, using AI not only to be efficient, but also to learn, innovate, and be competitive in the long run [58].



Future Directions

Artificial Intelligence (AI) and Lean Six Sigma (LSS) integration is still in its initial stages and is yet to be fully utilized in industries. The further evolution of AI-based LSS will be defined by the enhanced technological integration, high levels of automation, and closer human-machine cooperation as organizations embark on their digital transformation journeys. This part summarizes the major future directions that can lead practitioners and scientists in the development of the field, reveal the trends and gaps in research and the implications of the Industry 5.0 in general [59].

The upcoming wave of AI technologies: generative AI, reinforcement learning, digital twins, and edge computing will even empower Lean Six Sigma approaches. Generative artificial intelligence can also help to solve problems by creating optimal process optimization plans and simulating the situation of improvement [60]. LSS solutions can be refined in real time through the use of digital twins, or virtual versions of physical systems, without interfering with real operation. In the meantime, reinforcement learning allows systems to constantly learn based on the feedback of the processes, which helps them to control and optimize the process autonomously. The intersection of AI and the Internet of Things (IoT), as well as Big Data analytics, will also supply more detailed and fresh information to LSS applications to power predictive and prescriptive decision-making [61].

The next step in AI-LSS development will be the integration of AI-LSS with other performance improvement and sustainability models, which is likely to be pursued by the future research and industry practice. The integrated approach to LSS and Total Quality Management (TQM), Agile methodologies, and Sustainable Manufacturing can develop more resilient and holistic systems [62]. The inclusion of Environmental, Social, and Governance (ESG) measures into AI-LSS models can help to align process improvement with the sustainability objectives. By introducing AI-based LSS into smart factories and cyber-physical systems, the implementation of intelligent manufacturing ecosystems will only accelerate, which will facilitate flexible and adaptive production models [63].



Despite these achievements, there are still great gaps in research. Existing research tends to concentrate on discrete applications as opposed to wholesome models that integrate AI technology in the Lean Six Sigma approach. Subsequent studies are needed to come up with standardized AI-LSS integration models, define maturity assessment tools, and come up with performance measurement metrics to be used to determine the outcome [64]. More longitudinal and cross-industry studies that would investigate the impacts of adopting AI in the long run on process capability, employee engagement, and organizational learning are also necessary [65].

Going forward, the development of Industry 4.0 to Industry 5.0 will be more focused on the collaboration of humans with AI, personalization, and sustainability. Lean Six Sigma will be the strategic platform of integrating human ingenuity with machine smartness in this new era. Data-intensive processes, predictive modeling and self-controlled tasks will be conducted by AI, whereas the strategic decision-making, ethical regulation, and innovation will be performed by humans [66]. The idea of the Smart Factory where systems are interconnected and optimize themselves on the basis of AI will establish itself as the new standard of operation excellence [67].

Conclusion

The intersection of Artificial Intelligence (AI) and Lean Six Sigma (LSS) is a revolutionary conceptual change in the quest to achieve operational excellence, continuous improvement, and intelligent decision-making in the business world. This has been reviewed by looking at the development, adoption, advantages, and obstacles of incorporating AI technologies in the classical Lean Six Sigma model that has seen how this integration is transforming the contemporary business processes. The results emphasize the idea that even though AI is the factor that improves the analytical and predictive capacity of LSS, the human factor, including leadership, culture, and knowledge, is at the center of the successful implementation.

The concept of lean six sigma is not new; it has been used as a pillar of quality management and improvement of processes with the aim of reducing waste, minimizing defects, and creating customer value. But in a world where complex data systems and high-rate technological change are the order of the day, traditional LSS tools tend to be limited in the analysis that they can



provide. AI addresses this gap because it will allow analyzing data automatically, recognizing patterns, and optimizing the process in real-time, complementing and extending the principles of LSS. AI can be used to add speed, accuracy and flexibility to all stages of the DMAIC cycle by applying machine learning, natural language processing, computer vision and predictive analytics. This gives it a better version of Smart Lean Six Sigma where smart systems are constantly learning and making processes more intelligent.

As the industrial applications described in this review suggest, AI-based LSS applications have brought tangible gains in various industries. The AI-advanced process control and predictive maintenance have been utilized by manufacturing industries to minimize downtime and defects. The healthcare systems have utilized AI analytics as part of LSS systems to enhance patient outcomes, minimize medical errors, and simplify workflow. On the same note, AI-enabled Lean practices have assisted service and financial organizations to enhance customer satisfaction and operational efficiency. These cases prove that there is no single field of AI-LSS integration, and it is a flexible, universal method enabling the digital transformation of the industrial scope.

Regardless of these developments, the review also noted that there are major obstacles that prevent the widespread implementation of AI in LSS. There are ongoing technical issues like low quality of data, integration problems and lack of interoperability. The resistance of an organization, cultural inertia, high costs of implementation and lack of skilled professionals slow down the progress as well. Further, ethical and legal issues such as data privacy and algorithm bias are also an issue with other risks that organizations need to approach responsibly. All these difficulties demand a comprehensive approach that includes the investment in digital infrastructure, cross-disciplinary cooperation, and lifelong education of workers.

In the future, AI and Lean Six Sigma will change as the overall industrial shift to Industry 5.0, where human and machine cooperation are prioritized, sustainability, and resilience are observed, will occur. Most LSS projects in the future will involve the use of advanced AI technologies including digital twins, generative AI, and autonomous process control to design smart and responsive production systems. Meanwhile, a human judgment and creativity will continue to play



a critical role in gaining AI insights and making sure that process improvements do not contradict organizational values and ethical standards.

In summary, AI-based Lean Six Sigma is a potent merger of an approach and technology that increases the ability of companies to attain operational efficiency in a multi-faceted world that is data-driven. When properly taken, it is not only more efficient and quality-enhanced but also innovative, learning and long-term competitive. There are some obstacles on the way to AI-enriched Lean Six Sigma, but its possible impact on the continuous improvement and quality management cannot be disregarded. The organization that will manage to correlate the accuracy of AI and the strategic foresight of Lean Six Sigma, building intelligent, adaptive, and human-focused systems that will add to the sustainable success, will be the future.

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