Department of Industrial Engineering & Maintenance

AI Meets Lean Six Sigma: The Future of Operational Excellence

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Abstract: This article explores the use of Artificial Intelligence (AI) within the framework of Lean Six Sigma (LSS) through the DMAIC approach and its five stages, namely Define, Measure, Analyze, Improve, and Control for an improvement of quality management. In addition to increasing productivity, combining AI's predictive powers with LSS's methodical approach ensures that most, if not all, quality control standards are achieved. This leads to continuous improvement in a variety of industries where operational effectiveness is essential for sustainability and success. However, several companies tried to apply LSS, only a few of them have been successful in improving their operations to achieve the expected results. This research focuses on how AI -through Machine Learning (ML) models and data-driven approaches- improves each phase of LSS, from problem identification and data mining to root cause analysis and process optimization. In particular, neural networks, anomaly detection, ML algorithms, and digital simulations are described. It also outlines the issues that are associated with it (such as data privacy constraints, specialized skills requirements, and technical compatibility). To sum up, it confirms that applying AI to LSS enhances industrial process advances in efficiency, quality, and sustainability.

Key-Words: Lean Six Sigma, DMAIC, Operational Excellence, Data-Driven Decision Making, Artificial Intelligence, Machine Learning, Natural Language Processing, Computer Vision.

Contents

1. Introduction

To stay ahead of the competition, organizations are constantly looking for new and profitable ways to meet customer demands for fast delivery of high-quality products and services. This is a result of the emerging wave of competition well-proven by the constant growth and venturing of globalization [1, 2].

Over the last ten years, it has become a common phenomenon for the industrial sectors to experience dramatic changes due to technological innovation and customer demands. This has forced organizations to find ways to take advantages in the competitive dynamic markets. Artificial Intelligence (AI), being an innovative technology, has received a lot of attention by mimicking natural human intelligence and improving decision-making [3]. Lean Six Sigma (LSS) has been recognized for many decades as an effective methodology for implementing process improvements by combining Leans focus on waste reduction with Six Sigmas emphasis on minimizing defects. Recent advancements in AI, including Machine Learning (ML), Natural Language Processing (NLP) and Computer Vision, have opened new possibilities for enhancing these methodologies. AI can process vast amounts of data, identify hidden patterns, and deliver insights that are often difficult to detect using traditional methods. Integrating AI into LSS enables greater accuracy, speed and scalability in process optimization [4].

In particular, industrial AI focuses on practical, real-world applications such as increasing consumer value, accelerating predictions, and uncovering actionable insights. This synergy has become increasingly impactful due to the proliferation of affordable sensors, faster processing power, expanded data collection, and the rise of cloud computing, marking a transformative shift in how businesses improve performance and maintain competitiveness.[5].

However, the adoption of AI in real-world production is harder than it appears because industrial processes are complex and constantly changing. Unlike systems that only exist in the digital universe, real-world production involves both the physical and virtual aspects, so solid solutions are needed to handle uncertainties while keeping things reliable. The challenges come primarily from the production data itself, which tend to be messy, inconsistent and uncertain, making tasks - such as data integration, cleaning, and management- very challenging [6].

Studies have shown that Machine Learning (ML), in particular, holds great potential to significantly improve production quality [7–10]. These advances help companies to achieve their mission of providing high quality products by making policies based on defects predicted by the ML procedures, detection [11] and product quality prediction [12].

In this study, we're exploring the revolutionary potential of integrating AI with LSS. We will demonstrate how Artificial Intelligence tools, such as ML and NLP, may improve each stage of the DMAIC (Define, Measure, Analyze, Improve and Control) methodology. Instead of treating AI and LSS as separate entities like other studies, were laying out a practical guide for combining them into a synergetic work methodology. We'll tackle important issues like data quality, team readiness, and tricky ethical questions. With real-world case studies and hands-on analysis, were going to demonstrate how integrating AI in LSS not only increases efficiency and cuts down on defects but also sets the stage for smarter, greener manufacturing in the industry 4.0 era.

With this aim, this article is structured into five sections, starting with a brief introduction in Section 1. Section 2 provides a quick literature review of the current state of the art of using AI in LSS by exploring different research experiences in this field. Section 3 introduces the background needed to understand this research. Section 4 describes the impact of AI in each phase of the DMAIC approach. Following that, Section 5 presents the benefits of integrating AI in LSS and Section 6 highlights some case studies about the subject. Sections 7 and 8 respectively showcase the limits of this research and a simple conclusion of the study.

2. Literature Review

In this section, we selected scientific articles from well-known databases such as IEEE Xplore, ScienceDirect (Elsevier), and Emerald Insight. The articles were chosen because they talk about LSS and how it is used with new technologies, especially in Industry 4.0 and AI. To find the right articles, important keywords like "Lean Six Sigma," "Industry 4.0," "Artificial Intelligence," "Continuous Improvement," and "Digitalization" were used. The selection focused on studies that give clear methods, reviews, or real-life examples related to modern industry. Articles that were only theoretical and not connected to practical or technical use were not included.

Integrating AI with Six Sigma (SS) creates a powerful synergy for process optimization. The strength of SS in structured, data-driven analysis is enhanced by AIs advanced capabilities, particularly in automation and predictive analytics [13]. This integration makes decision-making quicker and more accurate, while also supporting continuous improvement by reducing mistakes that come from manual work.

The success of this integration lies in their shared reliance on data-driven insights and continuous improvement. AI can handle large amounts of data quickly, it a natural fit for the LSSs DMAIC framework. It helps find inefficiencies and patterns that traditional methods might miss[14] [15].

Usually, SS involves manual data collection and interpretation, which is time-consuming and prone to human error. AI automates this process, delivering faster and more precise results. Also, ML adds extra value by spotting potential problems early, so teams can address them before they turn into bigger issues [16] [17]. AI also supports real-time monitoring that accelerates up the improvement cycle and enables for the quick identification of deviations. Additionally, the automation of data analysis reduces human error and ensures standard SS implementation across departments [18].

2.1. Related Research

In the following table, a global overview of related research -to this study- is presented.

Table 1: Summary of some selected articles in the literature review

Title	Author(s)	Techniques	Objective
Process Optimization in a Condiment SME through Improved Lean Six Sigma with a Surface Tension Neural Network	Manuel Vargas et al [19]	ML , ANN	A hybrid Lean/Six Sigma model utilizing a Surface Tension Neural Network (STNN) was implemented to control temperature and relative humidity in real-time.
Optimizing Beverage Manufacturing: Integrating Lean Manufacturing and Machine Learning to Enhance Efficiency and Reduce Waste.	Raul Mendoza-Sotomayor et al [20]	ML	Proposes a model that integrates Lean Manufacturing and Machine Learning to optimize the production process, reduce line change times and reduce the percentage of waste.
Improving plastic manufacturing processes with the integration of Six Sigma and machine learning techniques: a case study.	Abd Elnaby et al [21]	ML , ANN , KNN , DT	This research aims to integrate machine learning techniques with the Six Sigma DMAIC methodology to reduce production defects, enhance product quality, and optimize manufacturing costs in plastic bottle production at the Innovative Plastic Manufacturing Company in Egypt.
LSS 4.0: A Conceptual Framework for Integrating Lean Six Sigma and Industry 4.0 for Smart Manufacturing Excellence	Chadha, U., et al[22]	ANN , DT , SVM , GP	Proose framework LSS 4.0 to enhances process reliability, prevents defects, and improves operational performance
The Application of Machine Learning to Consolidate Critical Success Factors of Lean Six Sigma.	ACHINTHYA D. PERERA et al [23]	DL , ANN , NLP	Proposes a model that combines Lean Six Sigma and Machine Learning to streamline key success factors, boost business efficiency, and enhance customer satisfaction through data-driven insights and predictive analytics.
Prediction in Industry 4.0 with Lean Six Sigma	Goyal et al [24]	ML ,NLP	This research aims to highlight the impact of artificial intelligence (AI) on Lean Six Sigma strategies, demonstrating how AI enhances its methodologies and accelerates organizational transformation toward Industry 4.0 without replacing the foundational principles of Lean Six Sigma.
Lean Six Sigma 4.0 Application in the Food & Beverage Industry : A Case Study	Wellington Quirino dos Santos, et al [25]	ML , ANN , NLP	integration of lean six sigma and machine learning and create of predictive lean six sigma to enhance Operational Equipment Effectiveness (OEE) in a Food Industry Manufacturing Site
Predictive Six Sigma for Turkish manufacturers: Utilization of machine learning tools in DMAIC	Uluskan M, Kar MG et al [26]	LSS, ML, KNN, ANN, GBM, RF	This study aims to emphasize utilization of Predictive Six Sigma to achieve process improvements based on machine learning (ML) techniques embedded in define, measure, analyze, improve, control (DMAIC)

3. Background

This section briefly introduces the background of the two main topics studied in this paper. Lean Six Sigma (LSS) and Artificial Intelligence (AI) Tools.

3.1. Lean and Six Sigma

Lean manufacturing, originating from the Toyota Production System (TPS), is the source of the innovative Japanese management model that focuses on using minimal inventory and high flexibility. The idea first surfaced in the years following World War II, when Japanese businesses were struggling to reach Ford-like levels of efficiency, which were known for their cost-effective and waste-free operations[27], which consequently became a guiding principle for activities aimed at delivering customer value and eliminating waste [28]. These situations forced companies to operate in accordance with Lean Manufacturing principles, this eventually evolved into a foundational principle for projects aimed at delivering customer value and minimizing waste.

At Motorola Corporation, Bill Smith first proposed the idea of Six Sigma in 1980 with the goal of lowering errors and defects by using the DMAIC approach [29]. DMAIC refers to a data-based lifecycle approach that ensures an organized, logical and efficient sequence of operations in project management. Its objective is to identify, quantify and minimize sources of process variation [30] through the utilization of statistical quality tools for data collection and analysis that facilitates sustainable decision-making in process-related inquiries.

According to George and Michael L. [31], merging LSS methodologies is crucial for reducing costs and complexity. While Lean focuses on process speed and capital reduction, Six Sigma alone may not provide the statistical control required. Alternatively, the objective of LSS is to minimize waste, enhance performance, and contribute to customer satisfaction [29]. It is crucial for all individuals within an organization to understand and implement concepts of this methodology, which can be regarded as a business strategy [32]. By addressing hidden costs of complexity, LSS ensures engagement from all stakeholders, enabling the establishment of a range and quality without compromising speed and cost [31]. Furthermore, the integration of Lean principles with the DMAIC approach, allows companies to solve workflow bottlenecks systematically, improve quality and deliver sustainable results across a wide range of projects and initiatives.

3.2. LSSs DMAIC Methodology

The LSS system demonstrated by DMAIC is a structured approach that helps solve existing problems, see future opportunities and manage projects [33] [34]. DMAIC can filter a complex problem with many uncontrolled variables to a situation where quality is controlled. DMAIC has proven to be one of the most effective problem-solving methods used up to now, because it forces the teams to use the data to do the following [35].

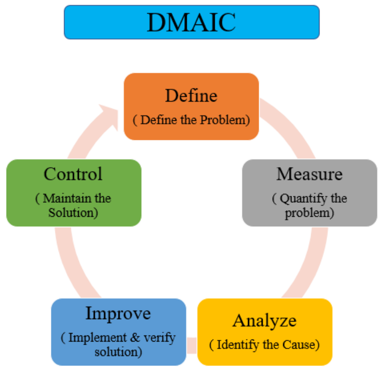

Figure 1: Overview of DMAIC Phases

3.3. AI Applications

AI has been booming, and within the last decade there have been many computer-integrated studies in the various aspects of the manufacturing industry [36].

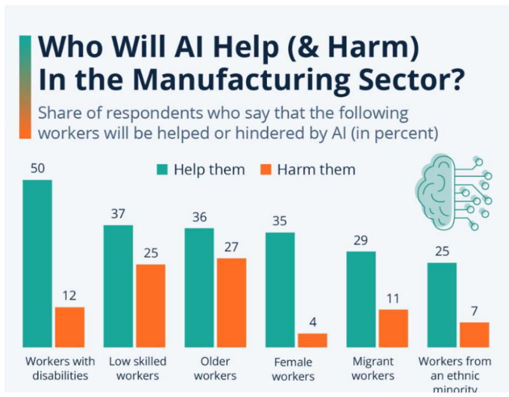

Figure 2: "Who Will AI Help (& Harm) In the Manufacturing Sector? A Statistical Study by Statista [4]

A study of 61 countries found that using AI in factories helped increase their performance in global markets by over 1% between 2000 and 2019 [37]. Another study showed that smart factories using AI have less downtime and better-quality products [38]. While using AI needs investment and training, its benefits are making manufacturing smarter and more competitive.

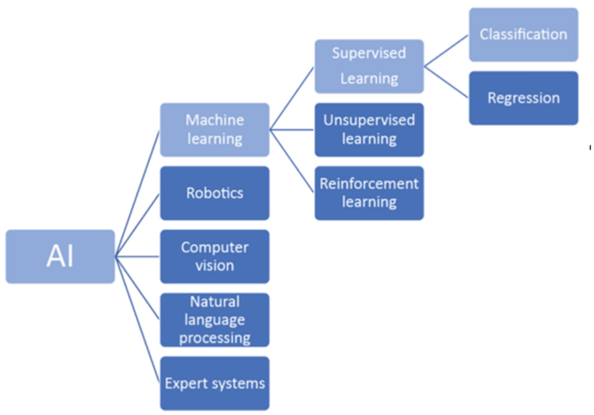

Figure 3: Areas of AI [39]

3.3.1 Machine Learning (ML)

Broadly speaking, ML is the science of computers running without being explicitly programmed [40]. It applies a series of statistical techniques, such as mathematical modelling, data visualization, and pattern recognition, to conduct self-learning activities with input data to predict and understand data trends and patterns [41, 42]. Recent applications of ML include corporate revenue forecast analysis and investment decision-making. For example, Two Sigma Investments LP -a New York City international hedge fund-works with vast sets of big data from over a thousand diverse sources and uses ML to build powerful investment predictive models [43]. Other applications of ML in the business world include the prediction of consumers purchase intentions, as widely used by Amazon and Taobao [43].

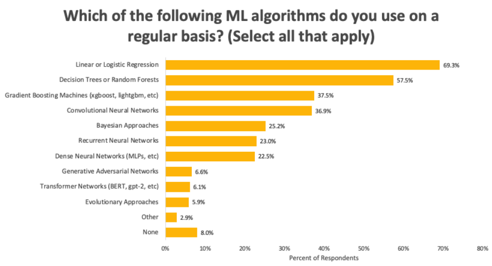

Figure 4: Most Used ML Algorithms

In the practice of management accounting, ML could assist in transactions classification with the scope of the control function, such as in financial planning and analysis (FP&A). The use of an ML application technology allows the prediction of transaction classification based on the analysis of financial history. However, the quality of the prediction depends on the quality and inherent bias of the data set utilised [44]. An example of transaction classification is an email communication tool that classifies marketing and promotion to consumers as 'advertising expenditure' and employee communication as 'IT or communication'. ML technologies can be trained to recognize the difference and clarify each category with a pre-set algorithm. In the practice of tax administration, the Guangdong Provincial Taxation Bureau adopts ML approaches to identify suspected fraudulent tax practices [45].

3.3.2 Natural Language Processing (NLP)

NLP focuses on understanding unstructured data (from human sources) as an application of AI. Examples of NLP include text mining, manual text analysis, and readability analysis [46, 47]. NLP is used to find evidence for strategy making based on the market environment and consumer activities. Unlike traditional internal auditing, NLP technology can automatically process unstructured text information, retrieve and review the main points of review systematically and automatically, so that internal auditors are free from heavy reading and review work. At the same time, the language model can identify high-risk cases that do not meet the target terms and issues and perform a preliminary screening for internal auditors so that they can focus on high-risk cases and perform in-depth follow-up to achieve efficient internal audit work [48].

3.3.3 Computer Vision

Computer Vision, an active AI discipline, enables machines to interpret and analyze visual data much like human eyesight [49]. Drawing from Computer Science, Mathematics, Physics, and Machine Learning, it powers applications such as image classification, object detection, semantic segmentation, and 3D scene reconstruction. These days, Deep Nets, especially Convolutional Neural Networks and the hot new Vision Transformers are stealing the show, but the old-school feature methods (SIFT, SURF) still do a ton of heavy lifting [50]. Lately, folks are pushing the envelope with self-supervised approaches that learn without hand-labelled data and blending vision with language models to get machines chatting about what they see [51].

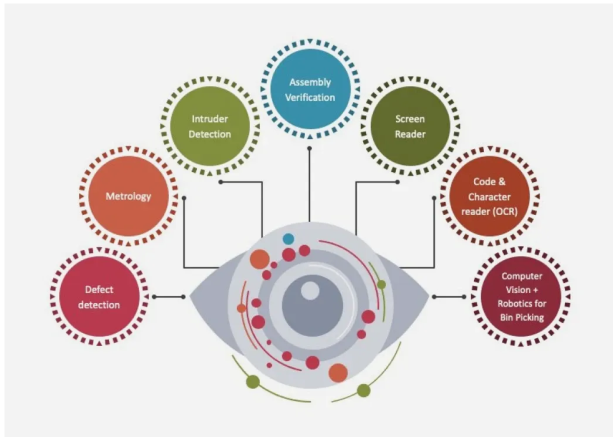

Figure 5: Applications of Computer Vision

4. AI Integration in LSS's DMAIC Phases

The integration of AI into the LSS's DMAIC methodology creates new prospective opportunities to improve processes with the help of data-driven decisions that are made with speed and scope that are impossible with ordinary tools and methods [15]. AI improves every phase of DMAIC, allowing organisations to improve accuracy, effectiveness, and sustainability in continuous process improvement programs.

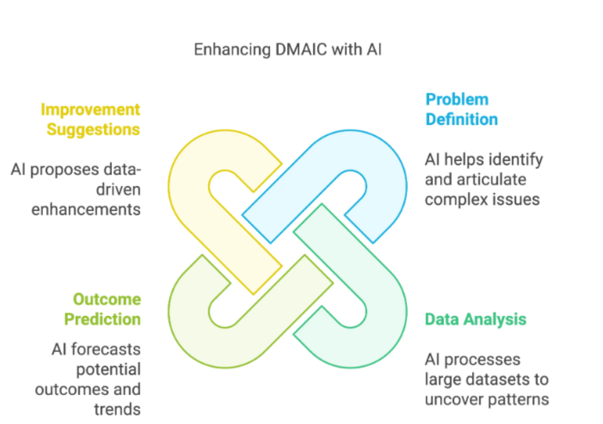

Figure 6: Enhancing DMAIC with AI

4.1. Phase 1 : Define

In this phase, AI helps in better identification of problem areas and objectives of the project through data mining and analysis methodologies including clustering and other ones as Principal Component Analysis (PCA) [14]. These strategies help teams to manage large amounts of data, automatically find inefficiencies, and critically identify problem areas that may not be easily detected by traditional strategies. It also enhances customer voice analysis by applying NLP since these technologies extract information from questionnaires, social media, and online reviews... Deep Learning (DL) Models, including transformers and Recurrent Neural Networks (RNN), are used to frequently identify trends in consumer complaints in sentiment analysis. This AI-driven approach not only reduces manual effort but but also provides more accurate and suitable definitions of problems based on real-customer data [52].

4.2. Phase 2 : Measure

This second phase requires precise and fast data gathering, which is an area where AI stands out [13, 16]. AI-powered solutions offer access to up-to-date, comprehensive datasets by delivering data in real-time from sources like cloud platforms, ERP systems, and IoT devices. Modern sensors and ML models collect both structured and unstructured data in order to offer a more accurate monitoring of operations. Based on factors like moisture, temperature, or operational conditions, AI helps keep data accurate by using anomaly detection methods such as auto-encoders. These can automatically detect values that deviate from expected patterns and fix incorrect data in real time. With positive reinforcement learning systems, data-collection methods can be improved to create strong, dependable, and steady datasets, while reducing human errors [52].

4.3. Phase 3 : Analyze

AI accelerates the Root Cause Analysis (RCA) of this phase. ML methods like Stochastic Forests, Decision Tree Models, and Support Vector Machines (SVMs) have made it possible to sift through large volumes of data to uncover key drivers of errors or inefficiencies. These models are capable of spotting trends that can go unnoticed through traditional statistical processes, allowing quicker identification of root causes [16]. In addition, it provides association rule learning techniques like the Priori Algorithm that uncovers complex dependencies between process variables leading to a deeper understanding of process behaviour. In addition to RCA, AI-enabled analytical models are able, if it is requested, to predict potential future problems. Time-series forecasting methods -for instance, those utilizing Auto Regressive Integrated Moving Average (ARIMA) or Long Short-Term Memory (LSTM) networks- give firms the ability to predict and mitigate process errors, thus leading to more informed, strategic decisions [3].

4.4. Phase 4 : Improve

In this fourth phase, AI enables the virtual testing of potential changes before they are implemented in real operations. Instead of relying on fixed rules, AI can learn how to improve processes on its own by trying different options and seeing what works best. Methods like Reinforcement Learning (RL) or Evolutionary Algorithms help explore a lot of possible solutions without needing someone to test each one manually. For example, Neural Networks may be utilized to enhance production planning or supply chain management, balancing key trade-offs in real-time to ensure continuous improvement [53].

4.5. Phase 5 : Control

For this last phase, AI helps keep things on track by constantly checking performance through real-time data and spotting any issues early on. These systems can automatically spot when something goes wrong, making it easier to take corrective actions quickly. AI-powered Statistical Process Control (SPC) systems can even update control charts in real time, reducing the need for manual interventions. AI can create feedback loops that automatically adjust process settings based on changing conditions. For example, RL models can keep improving operations by learning from real-time data, ensuring long-term performance gains. Besides, Predictive Maintenance algorithms are capable of assessing equipment conditions, decreasing the chances of malfunctions and ensuring process reliability [54].

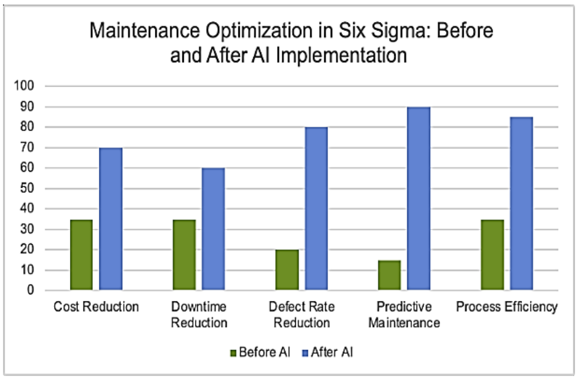

Figure 7: Maintenance Optimization in Six Sigma : Before and After AI Implementation

5. Benefits of Integrating AI in LSS

Lean Six Sigma -with the support of AI in data collection and processing, pattern recognition, and decision making-can greatly expand the portfolio of its applications. Incorporation of some aspects of Artificial Intelligence enables organisations not only to speed up problem solving, but also to get solutions that are enriched with deeper analytical perspectives from the data and as a result, the solutions are generally more accurate and sustainable. It also presents a great opportunity for resolving such important industry's issues as the improvement of efficiency, increase of predictive and monitoring analytics, and automation of decision-making process.

5.1. Automating Routine Tasks with AI

One of the most significant benefits of AI in LSS is its ability to automate routine and repetitive tasks. By freeing up human resources from everyday activities, we can focus on problem solving and innovation of higher value. Beyond basic automation, AI can also be used to automate more complex tasks, such as Process Mapping and RCA. Using ML, AI can identify patterns in processes' data to automatically generate process maps and potential root causes of defects. This can accelerate the problem-solving process and improve the accuracy of root cause identification.

5.2. Improving Quality and Defect Prevention

AI can play a crucial role in improving the quality of products and services by allowing early detection of defects and anomalies. Through the use of Computer Vision and Image Recognition, AI can inspect products for defects with greater accuracy and speed than human inspectors. This can help prevent defective products from reaching customers and reduce re-work costs. In addition, AI can be used to analyze customer feedback and identify emerging quality issues. Also, by monitoring social media and online reviews, AI can detect trends that indicate potential problems. This allows organisations to address issues proactively and prevent customer dissatisfaction.

5.3. Optimizing Workflows and Resource Allocation

AI can be used to optimize both workflows and resource allocation by analyzing process data and identifying bottlenecks and inefficiencies. By simulating different scenarios, AI can help in identifying the best ways to improve process flow and reduce cycle times. For example, in a healthcare setting, AI can be used to optimize patient flow through the hospital by analyzing patient arrival patterns, treatment times, and resource availability. This can help to reduce wait times, improve patient satisfaction, and increase bed utilization.

6. Case Studies

6.1. LSS and AI for an efficient production line at Jabil

To improve productivity and product quality, Jabil, a multinational manufacturing company, has integrated AI into its production processes. By applying ML techniques to analyze data from their manufacturing operations, the company has successfully identified bottlenecks and eliminated wastes, resulting in a more streamlined production and lower operational costs. Jabil has experienced a significant increase in productivity and a decrease in production costs as a result of this AI-driven strategy. One notable example is the 50% decrease in defect rates on one of their lines after addressing main root causes identified through data analysis. Additionally, the implementation of AI has improved Jabil's financial results. With reduced costs and higher yields, the company has strengthened its market position and improved overall customer satisfaction [55].

6.2. Improving plastic manufacturing processes with LSS and ML integration

This case study focuses on an Egyptian plastic manufacturing company that produces PET bottles and has important quality problems, including surface markings, bubbles, flashes, and irregular volume capacity. These defects led to high product rejection rates and increased production costs due to material waste. Using the DMAIC methodology, the team first identified that the PET bottle production line was the source of 95.7% of errors. Salt and impurity accumulation in the cooling system led the temperature controller into overheating, which was identified as the primary root cause. After applying chemical cleaning solutions and installing external water filters, defect rates were significantly reduced. ML models were used to anticipate and identify flaws in order to improve quality control even more. Among the tested models, the K-Nearest Neighbors (KNN) Algorithm showed the highest accuracy with an Rš value of 98.8%. As a result of the combined LSS and ML interventions,the Sigma Level of the process improved from 3.14 to 4.30, the defect rate dropped significantly,and material overuse costs decreased from 5% to just 1.7% of the total production costs. This led to improved product consistency, reduced waste, and better operational efficiency [21].

6.3. AI integration in Six Sigma documentation process of Pharma Firm

By adding AI into its Six Sigma documentation process, a famous pharmaceutical company aimed to improve its quality assurance procedures. The firm gathers, analyzes and reports crucial quality parameters throughout its manufacturing processes automatically by using ML algorithms and AI-powered data collecting systems. In order to anticipate probable deviations or flaws in manufacturing processes, ML models were built on previous data. This allowed for proactive interventions to avert quality problems. In order to reduce compliance risks and guarantee the integrity and correctness of paperwork, AI-driven validation checks were also put in place. Integration of AI through ML into Six Sigma documentation led to significant gains in productivity, accuracy, and adherence, thus encouraging continuous development and operational superiority inside the company [56].

7. Limits of This Research

The integration of AI with LSS has a positive impact on the improvement process, but it also introduces new obstacles and constraints. These include technology, operations, and workforce challenges that organisations need to overcome to support adoption.

7.1. Data Privacy and Security Concerns

The use of AI within the LSS infrastructure constantly involves recovering voluminous datasets that may carry sensitive information, corresponding to client details, operational metrics, or non-exclusive business data [57]. This raises substantial concerns regarding data privacy and protection. Besides, systems using AI, especially those utilizing cloud-based architectures, are more exposed to cyberattacks and data breaches [14, 57]. To secure sensitive data and comply with legislations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), organizations must employ robust security measures such as encryption, access limits, and data anonymization. These regulations govern how data is acquired, kept, and processed, making it more difficult to implement AI-driven LSS programs. Furthermore, privacy issues might limit the amount and type of data accessible for analysis, reducing AI's potential to provide meaningful insights.

7.2. Need for a Skilled Workforce and Training in AI and LSS

Another crucial difficulty is the necessity for a competent staff who understands both AI technology and LSS processes. AI systems need competence in Data Science, Machine Learning, and Algorithm Development, whereas LSS relies on a thorough understanding of process optimisation approaches. This dual skill set is uncommon, and organizations constantly have difficulties locating staff who can navigate both areas. As a result, companies may need to spend significant employee training or recruit specialised experts, adding costs and delaying fulfilment. Also, successful AI integration into LSS requires strong change operation tactics to overcome opposition from workers who may be inexperienced with or sceptical of AI [58]. Creating thorough training programs that bridge the gap between AI professionals and LSS experts is critical for encouraging collaboration and assuring that teams can operate productively together.

7.3. Technical Challenges in Integrating AI with Existing LSS Practices

One of the key technical hurdles in merging AI with LSS is the integration of AI technologies with existing legacy infrastructures that most organizations already have in use [58]. Many organizations use outdated technologies that may not be compatible with new AI tools, causing problems with data collecting, processing, and analysis. Moreover, AI implementation frequently brings about huge expenditures in cloud computing, high-performance computer infrastructure, and data storage, which might be prohibitively expensive for firms that are not yet technologically competent. Aligning the outputs of sophisticated AI algorithms, such as those used in Deep Learning or Neural Networks, with LSS's structured DMAIC methodology can be difficult for practitioners new to AI. The technical complexity of installing, maintaining, and interpreting AI models needs the engagement of highly experienced humans, which represents another consequent difficulty.

7.4. Ethical Considerations

Another challenge of implementing AI in LSS is ensuring that the models are used ethically and do not discriminate against certain groups of people. As AI systems become more prevalent in decision-making processes, it becomes increasingly important to consider the ethical implications of their use. This includes issues such as bias, fairness, and accountability. AI models can inadvertently perpetuate biases and discrimination if the data used for training the models is not representative of the population it is intended to serve. To ensure that AI systems are used ethically, companies can implement guidelines and protocols for a more responsible AI development and use. Organizations like the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems provide such guidelines. Companies can also use techniques such as bias detection and correction, data cleaning, and algorithmic transparency to ensure that their AI models are transparent and accountable. Additionally, they can also establish a strong governance framework and ethical guidelines to ensure that their AI systems are aligned with their values and principles.

7.5. Workforce Disruption and Adaptation

The technologies are still evolving, especially AI and Blockchain. While the AI boom is ongoing, there are still some flaws and backlog developments in the technologies that researchers have to work on. There are various blind spots where even humans cannot understand or regulate the AI models they are using. The AI models are supposed to be regulated and not overdeveloped to create their own language of communication which is not understood for the humans. As cited by Elon Musk in the news, AI should be judiciously regulated and its overdevelopment can also lead to problems where it could outsmart humans. This claim was impractical until the speculation and actualization of an AI revolution in the past few years using the Large Language Models (LLMs) as the first stepping stone, which has started taking various jobs within the IT sector. Nowadays,it is practical to say that AI can affect the jobs in the manufacturing industry of the future [59]. Simulations to machine operations were regulated by AI so that there is a possibility that human involvement will be considerably decreased in the manufacturing industry, which will only demand skilled workers and reject the labor jobs as a whole. While this is good for the society perspective to increase the skillset, it could also lead -on a humanitarian ground sit- to a crisis where education is still a beat of the farther land. Even though the humanitarian and AI induced issues are not the scope of this study, but it is also an inevitable factor, that is an essential part of such discussions of advantages and disadvantages that goes beyond just the skills training of the employees.

8. Discussion and Conclusion

This study explains how the DMAIC phases of LSS can significantly improve the efficiency of each phase through the integration of modern techniques and technologies. It illustrates how different methods optimize the process, from the definition phase, which uses data modelling and natural language analysis, to the control phase, which implements quality control systems and predictive maintenance plans.
In this article, we explored how numerous advanced modelling approaches, such as Deep Learning, supervised techniques like Decision Trees and Reinforcement Learning, can improve analysis and decision-making and reduce variability. These methods provide flexible tools for predicting, simulating, and optimizing global operations while also en-

abling faster data processing and deeper analytics.

Our investigation has also shown that the synergy between AI and LSS is not only theoretical but already being applied in industrial settings, particularly in data-intensive environments. The increasing availability of IoT data, cloud infrastructures, and advanced algorithms facilitates real-time integration and immediate responsiveness, which are critical for modern manufacturing and service systems.

However, integrating AI with LSS requires a strong digital infrastructure and a serious attention for ethical and data privacy issues. Its also important to remember that these tools are built to support people, not take their places.

In order to assess the long-term effects of AI-driven DMAIC activities across various industries, more empirical validation is advised. In particular, future case studies could focus on how specific AI models influence Key Performance Indicators such as defect rates, lead time, or customer satisfaction.

Moreover,To integrate AI effectively into Lean Six Sigma, organizations need to be well prepared. This includes strong data protection, regular training for employees, and attention to ethicslike being transparent and responsible with AI decisions. These steps help make sure AI supports people in a safe and useful way. In the future, flexible AI models and real-time data analysis could make continuous improvement faster, more predictive, and more automated. To keep up, companies will need to stay open to change, encourage innovation, and build teams that can quickly adapt to new technologies.

Looking ahead, future research could explore how AI can support faster and smarter decision-making in real-time production settings, especially by using technologies like predictive analytics, deep learning, and process mining. There is also a need to design AI tools that are user-friendly and accessible to employees without strong technical skills, for example through visual dashboards, natural language interfaces, or automated data analysis. Another important direction is to study how organizations can prepare for AI-LSS integration by improving their data infrastructure, training staff in digital skills, and encouraging collaboration between data scientists and process improvement teams. In addition, more research is needed to understand the impact of AI-supported DMAIC cycles on key performance indicators such as defect rate, process lead time, energy consumption, and customer satisfaction. Finally, with growing attention to sustainability, future studies could investigate how combining AI with LSS can help industries reduce waste and carbon emissions while maintaining high quality and operational excellence.

To conclude, this research shows that integrating AI within LSS is not just a technological trend but a strategic direction that could redefine the standards of continuous improvement in the industry of future.

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A. Appendix

List of abbreviations :

- AI : Artificial Intelligence
- ANN : Artificial Neural Networks
- ARIMA : Auto Regressive Integrated Moving Average
- DL : Deep Learning
- DMAIC : Define, Measure, Analyze, Improve, Control
- DT : Decision Tree
- ERP : Enterprise Resource Planning
- GP : Gaussian Process
- GBM : Gradient Boosting Machine
- IoT : Internet of Things
- IT : Information Technology
- KNN : K-Nearest Neighbours
- LLM : Large Language Models
- LSS : Lean Six Sigma
- LSTM : Long-Short Term Memory
- ML : Machine Learning
- NLP : Natural Language Processing
- PCA : Principal Component Analysis
- PET : Poly Ethylene Terephthalate
- RCA : Root Cause Analysis
- RF : Random Forest
- RL : Reinforcement Learning
- RNN : Recurrent Neural Networks
- SIFT : Scale-Invariant Feature Transform
- SPC : Statistical Process Control
- SS : Six Sigma
- SURF : Speeded Up Robust Features
- SVMs : Support Vector Machines
- TPS : Toyota Production System