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Exploring the Integration of Artificial Intelligence into Lean Six Sigma Methodologies: A Roadmap for Enhancing Manufacturing Efficiency and Quality

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Abstract. *Combining artificial intelligence (AI) together with Lean Six Sigma (LSS) methods, especially the DMAIC framework (Define, Measure, Analyse, Improve, Control), has become a revolutionary way to make manufacturing processes better. This study looks at how AI and DMAIC can work together to improve operations. It focuses on how AI technologies can be added to each step of the DMAIC process. By applying artificial intelligence, prescriptive analytics, and simulation models, optimising process changes in the enhancement stage decreases cycle durations, minimises waste, and reduces related expenses. AI-powered real-time monitoring and automated alerts help the control phase stay consistent and reduce deviations by means of which it gains advantage. The research framework conceptually explains the development of DMAIC and the synergy among artificial intelligence tools. The data supports three main hypotheses H1) AI reduces variability and improves defect identification; H2) AI-driven analytics accelerates process enhancements; and H3) AI-based monitoring systems stabilise processes. Combining artificial intelligence with DMAIC provides the process of continuous growth that links operational performance to business objectives. This convergence improves manufacturing's competitiveness by facilitating more effective data-driven decision-making, process optimisation, and quality assurance.*

Keywords: Artificial Intelligence (AI), Industry 4.0, Machine Learning, Process Optimization, Lean Six Sigma Manufacturing..

Introduction

According to Endrigo Sordan et al. (2024), the integration of AI with LSS practices is being driven by the Fourth Industrial Revolution, which is enhancing manufacturing efficiency and quality. To boost process efficiency through decreasing variability and eliminating waste, Lean integrates manufacturing principles with Six Sigma methodologies. AI improves process optimisation, predictive maintenance, quality control, and decision support when applied to manufacturing.

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Figure 1 illustrates the numerous advantages of integrating AI with LSS methodologies (Skalli et al., 2024). as illustrated in Fig. 1.

Fig. 1. The synergistic integration of AI with Lean Six Sigma methodologies

Source: own research.

Strategic integration has greatly improved manufacturing performance and operational excellence. LSS and AI collaborate to revolutionise manufacturing processes, enhance operational efficiency, and set new standards for quality. Skalli et al. (2024) indicated that a study from the early 2000s demonstrated that organisations implementing LSS methodologies could decrease their production cycles by 30%. It has sometimes been difficult to get the exact information that is required in the current manufacturing environment using the traditional methods due to complexity and risk. This has implied that it is possible to create AI to overcome this challenge. For instance, sophisticated neural networks and machine learning algorithms are useful in analysing large data sets and patterns that are difficult for humans to identify. As indicated by Ly Duc et al. AI can measurably improve LSS solutions in manufacturing, AI-enabled solutions shrank defects from 6.5% to zero defects and led to 7.9% production throughput increase. The existing evidence suggests that manufacturing use-cases such as equipment failure prediction, supply chain logistics optimization, and agile decision-making can be addressed using real-time analytics. Also, "digital twins," essentially digital copies of physical production systems, are easier to create with AI. Manufacturers can use digital replicas to test and analyse process modifications in different scenarios without affecting real operations. Newly gathered data (Trubetskaya et al., 2023) shows that digital twins increased overall equipment effectiveness (OEE) and cut downtime by 10% for companies working on LSS projects. Preventative actions that decision-makers take in advance of possible problems allow them to save money and time and improve quality assurance protocols. On top of that, according to Sundram, et al. (2023), the DMAIC methodology becomes even more effective when artificial intelligence is integrated into it. According to Abd Elnaby et al. (2024), AI algorithms automate data collection and enhance the accuracy of root cause analysis, which improves every step. Tools powered by AI can drastically cut down on the time it takes to complete tasks that would otherwise take weeks or months for a thorough data analysis, according to several companies. This integration has enabled upgrades to real-time monitoring. According to a 2024 survey, 40% of manufacturing companies have implemented AI monitoring systems, resulting in an 18% reduction in quality control issues. Combining AI with LSS creates a setting where iterative improvement and continuous learning become the norm. There is increasing demand for manufacturers to increase their adaptability and resilience. As far as modern manufacturing practices go, the integration of AI with the time-honoured DMAIC methodology is a huge step forward. This analysis of the relevant literature shows that DMAIC has for a long time been a good way of improving pre-set processes. However, according to Abd Elnaby et al. (2023) and Sundram, Lian, et al. (2023), operational efficiency, quality control, and sustainability are all enhanced when AI is incorporated. The current AI tools enable the collection and analysis of large data sets within a short time. The incorporation of AI can boost the DMAIC approach's effectiveness by over 44% by identifying issues and implementing solutions before they arise. The method itself can enhance efficiency by up to 20%. The collaboration between industry and universities is a sustainable model of the manufacturing environment and its robustness and flexibility. Hence, the use of DMAIC with the help of artificial intelligence enhances the manufacturing systems to meet the customer needs and create sustainable value for the economy and environment. The literature shows that not all steps of the DMAIC framework incorporate artificial intelligence (AI). It is crucial to have a clear plan to integrate AI into all the components of the process, as some phases of the methodology can be enhanced by AI technologies. Despite these advancements, there remains a gap in understanding how to systematically incorporate AI into each phase of the DMAIC framework. This work intends to close this gap by creating a theoretical framework for the integration of artificial intelligence technologies in DMAIC and promoting standardised best practices in many different manufacturing sectors. The relevance of the study is underlined by the rapid development of AI technology and the growing pressure on manufacturers to implement Industry 4.0 techniques. Combining manufacturing, data science, and process improvement will help to inspire individuals from many sectors to collaborate and significantly increase the manufacturing sector's relative efficiency, better quality, and lower cost. We conducted the research to serve as a guide for future theoretical and applied research and production. To achieve this goal, we will highlight areas where research is lacking and demonstrate how integrating AI with DMAIC can yield significant improvements. This study employs a systematic literature review (SLR) to investigate the following research questions: In the DMAIC framework, how can the use of AI tools make the measurement and analysis phases more efficient and accurate than the use of traditional statistical methods? During the improvement phase, can process improvement initiatives be enhanced with simulation models and AI-driven prescriptive analytics? Do more stable and high-quality process outcomes result from the control phase of the DMAIC when AI is used to monitor and detect anomalies in real-time? A theoretical framework for incorporating AI technologies into the DMAIC methodology was the goal of this study. The goal is to maximise efficiency in the improvement process so that we can lower operational costs, increase product quality, and stay ahead of the competition in a dynamic industry.

Following this introduction, Section 1 conducts a comprehensive review of existing literature to establish the theoretical and empirical foundations of this study. Section 2 defines the methodology. Section 3 reviews the literature to map the theoretical framework, detail the findings, and synthesise the expert insights gained. Section 4 presents the study's contributions and outlines paths for future research.

Literature review

Driven by technological advancements and industry demand for better operational efficiency, the integration of AI with LSS in manufacturing has greatly advanced over the past five years. A lot of research has been done on how AI-based technologies could make traditional LSS methods better by making process changes more flexible and stable (Chiarini & Kumar, 20200.New real-world data shows that using AI with predictive analytics and machine learning speeds up and improves the quality of data analysis. Real-time data collection and analysis have enabled the detection of defects and consequently the assurance of quality as we collect the data. These techniques, as we shall see, also have the effect of reducing the downtime and, in a way, predicting the possible failure of the equipment. Another area of focus is automation. Robotic process automation (RPA) and AI-powered intelligent process automation (IPA) are vital to improving manufacturing processes (Siderska et al., 2023). Current developments indicate that the integration of these technologies with LSS enhances their productivity. For example, the continuous improvement of the process is ensured by automating routine tasks. These projects do it by eliminating the non-value-added activities and linking them with the fundamentals of lean methodology. It is therefore important that leaders are dedicated, willing to learn, and cross departmental, and open to the new way of thinking about technology to enable effective integration between AI and LSS (Skalli et al., 2024). The research of Sarath Kumar Boddu et al. (2021) and Costa et al. (2020) establishes that organizations that implement these systems are in a better position to create learning organizations that can effectively deal with changes in the market and operations. Artificial intelligence-driven predictive maintenance systems have greatly improved asset utilisation and dramatically reduced operational costs. This combined approach is likely to become more and more common in modern manufacturing strategies as technology progresses and will lead to further developments in a fast-changing business environment.

1. Process Improvement and DMAIC

Before the recent adoption of standard process improvement methodologies, like DMAIC, by the manufacturing industry, this paper finds that the industry has widely applied DMAIC to advance operational excellence. In the work of Sundram et al. (2023) real-life examples such as those given above clearly show that DMAIC is applied to improve product quality and process weaknesses and variability. In phase define and measure, it is very important to explain the process and determine its current state using the mapping tools to define the starting point. We systematically collect and evaluate cycle time, defects, and overall equipment effectiveness (OEE) to make informed decisions. This is because with well-defined measurement protocols, the process deficiencies are well established (Ly Duc et al., 2023). Statistical methods and techniques such as root cause analysis are an important part of the analysis phase during the application. It also reveals that manufacturers have been able to gain meaningful information from the complex process data sets using techniques like Pareto analysis and design of experiments (DOE). Several critical factors that can lead to a reduction in process variability by 15% to 20%. During the improve and control phase, subsequent improvement actions aimed at reducing waste, shortening the cycle time, and enhancing quality have resulted in more than 20% efficiency gains. In the control phase, implement checks and mechanisms to sustain the gains achieved. Many sources emphasise the crucial role of standardised work practices and frequent audits in maintaining process stability. According to research by Costa et al. (2020) DMAIC is a never-ending cycle of improvement that helps reduce risk and enhance manufacturing responsiveness.

2. AI in Manufacturing

AI technology has led to significant changes in the industrial sector.AI has been depicted positively in the literature especially by enhancing decision making and operational efficiency. Current research indicates the latest AI tools can make predictions about equipment failure through machine learning (ML) algorithms and real time sensor data analysis. Evidence can be provided for the effectiveness of both predictive maintenance and real time optimisation. The number of unexpected stops reduced by 19% and equipment reliability increased by 16% during the pilot projects where predictive maintenance models were applied. Khinvasara et al. (2024) opined that real-time data analytics can help in altering the process parameters, and this can lead to an improvement in quality control by 22%. This is because AI can provide real-time data analysis, which has enhanced the quality and process monitoring (Ionesi et al. 2021). The deep learning-based inspection systems can improve process dispersion by 17% and increase defect detection. Additionally, AI models also provide feedback loops that can be easily modified and can indeed prevent similar problems from happening again (Offmann & Reich, 2023). Thus, the application of artificial intelligence (AI) is crucial in supporting sustainable manufacturing practices like energy and material management through real-time monitoring. AI could increase production rates and decrease energy consumption. Thus, AI converts the raw data into valuable information, which helps manufacturers shift from a defensive approach to an offensive one, enhancing the use of resources and the quality of the product. This approach enables sustainable operations through cost reductions.

3. Integrated methodologies: DMAIC and AI in Manufacturing

When DMAIC combines with artificial intelligence, it transforms into smart and resilient factories that can adapt to market changes and sustain long-term environmental and financial benefits. This work will discuss the current state of the problem and the benefits of integrating artificial intelligence into the conventional DMAIC system. The several definitions and evaluations of this combined strategy offered in this work follow: This essay talked about how AI tools could make the DMAIC stages easier to define and evaluate. This way, businesses can use big data analytics to better define and evaluate the DMAIC stages and find trends that were hard to see before. AI can analyse real time data and find patterns and signals that conventional statistical methods may not discover. It can also monitor process performance over several cycles of control and improvement. According to Abd Elnaby et al. (2023) noted that the application of AI-driven algorithms would improve the root cause analysis (RCA) and forecasting during the analysis period. An experiment carried out to apply AI in setting quality and control limits till the process shown that the process stability could be improved by 21%. Integrated approaches can improve performance by 20–25% and advance environmental features including waste management and energy consumption. When combined with DMAIC, AI enhances sustainable development and stimulates innovation. Green technologies and the circular economy can be incorporated into monitoring and innovation through integrated systems, these methods are more environmentally friendly and economical. Using AI helps one to better gather, evaluate, and control data. Consequently, operational performance, quality control, and environmental management (Bhatta et al., 2022) see rather significant increases. Hybrid approaches are the way forward; the manufacturing of the future is one for a more flexible, strong, technologically advanced production system. This work aims to systematically review the contributions of the following papers, focussing on the integration of DMAIC and artificial intelligence to enhance the manufacturing process. This is resulting from the speed at which real-time adaptive intelligence is merging with structured analytical approaches to revolutionise the present sector. AI tools are integrated into DMAIC process improvement strategies, leveraging rigorous data collection, methodical approaches, and statistical analysis to define, measure, analyse, and control manufacturing processes. AI applies real-time data analytics, predictive maintenance, and machine learning to continuously monitor and control process parameters, thus cutting the costs of operation, production cycle, and defects, and to integrate well with conventional approaches. The DMAIC method can enhance efficiency by as much as 20 %. These advantages can enhance energy savings by more than 25% with the aid of AI. Sustainable manufacturing has the following as its goals: first, to state and implement policies for the maintenance of these advantages; second, to establish a standard for environmentally friendly manufacturing practices; and third, to improve processes and products continually. Thus, integrating DMAIC and artificial intelligence, manufacturing facilities produce products that can sustain as manufacturing facilities themselves become more intelligent, robust and agile to market changes

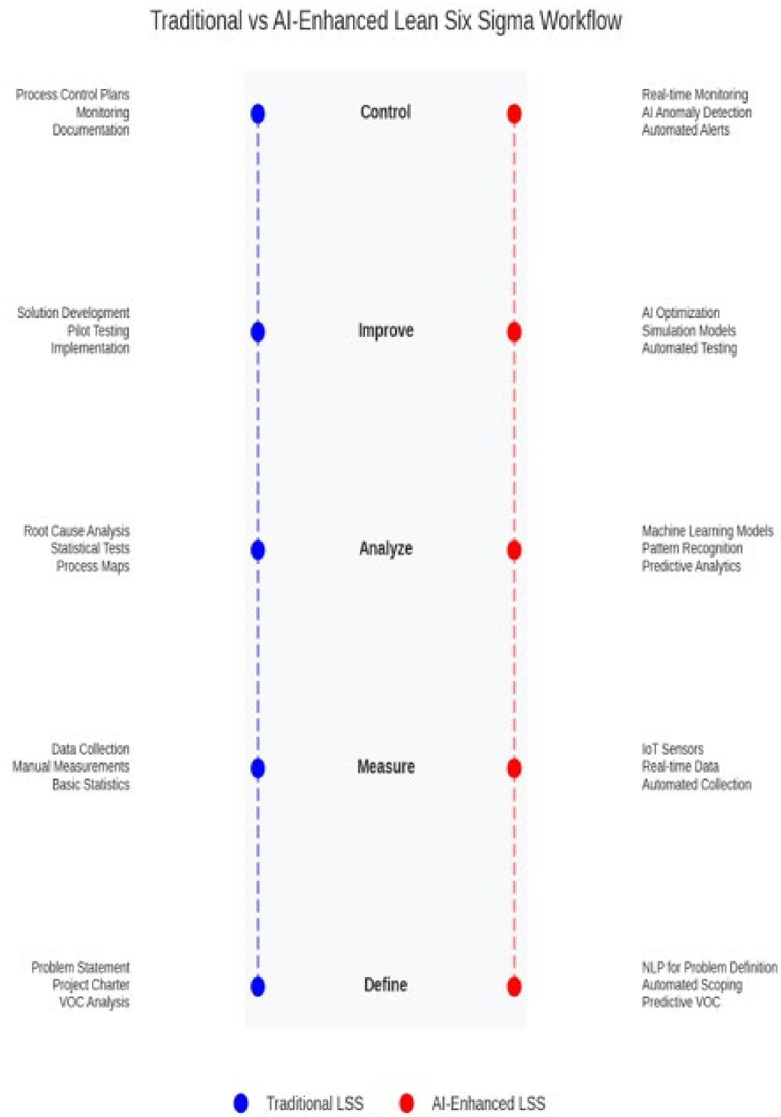

Fig. 2. The traditional Lean Six Sigma (LSS) workflow with the AI-enhanced LSS workflow, highlighting the differences in each phase of the DMAIC process

Source: own research.

Methodology

To establish the theoretical and empirical bases of this study, we carefully went over the body of current work. Our priorities were the following main ones:

Combine studies that show the DMAIC framework works well for leading LSS projects and consistently making manufacturing better. Critical challenges, such as inconsistent defect detection and process variability, have been identified in prior research. The papers and case studies emphasize the integration of artificial intelligence for data acquisition, Predictive Analytics, and Real-time Monitoring. Many studies have shown that AI is useful for predictive maintenance, quality assurance, and process optimization, among other things.

I reviewed papers that merged cutting-edge AI technology with popular process improvement frameworks (such as DMAIC) to determine whether the claims that the two can work together to boost performance were true. The body of research offers an understanding of the possible advantages, difficulties in applications, and scalability of AI-enhanced process management.

Through this review, three main hypotheses formed the study's conceptual framework.

H1: AI improves defect detection and reduces variability in the Measure and Analyze phases.

H2: AI-Driven Prescriptive Analytics enhance the effectiveness of process improvements in the Improve phase.

H3: AI-based Real-time Monitoring reduces process deviations in the Control phase.

Building on the literature, a *conceptual framework* was developed that integrates the DMAIC phases with AI tools. This framework visually and empirically maps interdependence among

DMAIC Phases: Define, Measure, Analyze, Improve, Control.

AI Tools: Including Data Integration, Advanced Analytics, and Real-time Monitoring.

Research Hypotheses: Each DMAIC phase supported by corresponding AI functionalities reinforces one of the study's main hypotheses.

This framework serves as the foundation for subsequent research design and empirical analysis.

This methodology integrates insights from the literature, operationalizes a well-defined conceptual framework to explore the transformative impact of AI-enhanced DMAIC processes in manufacturing.

Results and discussions

Table 1. highlights the key points of the review, which includes articles and case studies that explore the integration of artificial intelligence in data acquisition. There are research questions and hypotheses that are meant to investigate how artificial intelligence can be used with the Lean Six Sigma DMAIC framework in manufacturing

Research Question	Hypothesis	Key Components	Overall Implication	Conclusion
How can the integration of AI tools improve the accuracy and efficiency of the Measure and Analyze phases in the DMAIC framework compared to traditional statistical methods?	Integrating AI-powered Predictive Analytics into the Measure and Analyze phases of the Lean Six Sigma DMAIC methodology can significantly improve defect detection rates and process variability reduction compared to traditional statistical methods, according to a statement.	**Manufacturing processe**s involve various operations and activities, including machinery, labour, materials, and technology. **AI-powered predictive analytics** is used to forecast future consequences, including defects or inefficiencies. Current manufacturing systems implement this during the Measure and Analyze stages of DMAIC. **Data is collected during the Measure phase, and the Analyze phase** examines the root causes of defects. **Statistically significant improvements** in defect detection rates and process variability are confirmed through rigorous analysis. Higher defect detection rates lead to improved quality and reduced process variability, ensuring consistent and predictable results.	**Improved Defect Detection:** AI can analyse complex data patterns more effectively than traditional methods, leading to earlier and more accurate identification of potential defects. **Reduced Process Variability:** AI can facilitate more efficient identification of root causes of variability, enabling targeted interventions that stabilize the process and enhance consistency.	AI application in manufacturing can significantly enhance quality, efficiency, Lean Six Sigma effectiveness, customer satisfaction, cost reduction, and operational performance.

Research Question	Hypothesis	Key Components	Overall Implication	Conclusion
Can AI-driven Prescriptive Analytics and simulation models enhance process improvement initiatives during the Improve phase of DMAIC?	AI-based Prescriptive Analytics can expedite the identification of optimal process modifications, leading to a significant reduction in cycle times and waste compared to traditional Lean Six Sigma methodologies.	**AI-Driven Prescriptive Analytics** uses artificial intelligence to analyse data and recommend actions for desired outcomes, such as process changes or resource allocations. **Simulation Models** simulate manufacturing processes, allowing organizations to test scenarios and evaluate improvements before real-world implementation. **The Improve Phase of DMAIC** focuses on identifying, testing, and implementing solutions to address root causes of problems identified in the Analyse phase.	**Faster Identification of Optimal Process Modifications:** Traditional Lean Six Sigma methodologies often rely on manual analysis and historical data, which can be time intensive. AI possesses the capability to process large datasets rapidly, uncovering insights that might require significantly more time to discover through conventional methods. **Greater Percentage Reduction in Cycle Times** **and Waste Levels:** This component of the hypothesis proposes that the modifications identified through AI analytics will not only be implemented more rapidly but will also prove more effective in reducing cycle times (the total duration from the initiation to the conclusion of a process) and waste (unproductive resources or materials).	AI technologies can expedite manufacturing process improvement initiatives by utilizing prescriptive analytics and simulation models, reducing cycle times and waste, and potentially improving operational performance.
Does the real-time monitoring and anomaly detection capability provided by AI enhance the Control phase of DMAIC, leading to more sustainable process stability and quality outcomes?	AI-powered continuous monitoring and automatic warning systems in manufacturing processes are expected to reduce process variations and improve operational quality, potentially enhancing the Control stage of DMAIC.	**Real-time Monitoring:** This is the ability to keep track of and gather information from manufacturing processes as they occur. AI technologies, for instance, including machine learning algorithms and internet of things (IoT) sensors, can look at this data in real time to identify patterns, trends, and variations. **Anomaly Detection**: requires the identification of unusual patterns or deviations from the normal behaviour of the data. For instance, a higher-than-allowed temperature	**Real-time AI Monitoring:** It is the use of artificial intelligence for the online supervision and evaluation of manufacturing processes. It covers observations of equipment performance, product quality, and environmental conditions. **Automatic Notification Systems:** These are mechanisms that instantaneously inform operators or supervisors when anomalies or deviations are detected. **Statistically Significant Decrease in Process Variations:** This indicates that the implementation of AI monitoring	AI technologies can enhance DMAIC framework control by providing uninterrupted monitoring and instant anomaly alerts, leading to fewer deviations and improved quality outcomes over time.

Research Question	Hypothesis	Key Components	Overall Implication	Conclusion
		may point to a failure or a breakdown of the machine. AI can actively detect these anomalies and send them to the relevant people so they can act on them. **Control Phase of DMAIC:** The Control phase is concerned with the sustainability of the improvements made in the Improve phase and the sustainability of processes within the desired limits. This implies tracking of KPIs and the establishment of control policies to minimise or prevent variation. **Sustainable Process Stability and Quality Outcomes:** Sustainable process stability means that the manufacturing process consistently operates within desired parameters over time, leading to fewer defects and higher quality products. Quality outcomes refer to the overall effectiveness of the manufacturing process in meeting quality standards.	and alert systems is anticipated to result in a quantifiable and substantial reduction in process deviations from established standards. **Long-Term Enhancement of Operational Quality:** This suggests that the quality of manufactured products will consistently remain high over time, due to ongoing monitoring and swift responses to emerging issues. This can be evaluated using metrics such as defect rates, customer dissatisfaction reports, and overall equipment effectiveness (OEE). **Contrast with Intermittent Manual Quality Inspections**: This hypothesis suggests that conventional quality control methods, which rely on sampling inspections (e.g., hourly or daily inspections), may not be very effective in maintaining the process stability and quality. Some of these approaches may fail to recognise real-time problems and may lead to a time lag in solving the problems.	

Source: own research.

The results of this research indicate a strong correlation between the DMAIC phases and using AI tools. At every level, the DMAIC approach combines several AI capabilities.

Advanced Analytics and AI-driven Data Integration help to identify errors and process variability when it comes time for Measure and Analysis. This gives the theory that AI could enhance these features validity (H1). The second hypothesis (H2) holds that, when Prescriptive Analytics is applied during the Improve phase, process changes can be executed faster and with more efficiency. Real-time Monitoring and Automated Alerts help to improve the Control phase by progressively raising process stability and sharply Anomaly Detection. Including it into every stage of the DMAIC process helps to improve decision-making and generates a feedback loop maintaining the efficiency of manufacturing processes, so promoting the growth of fresh ideas. Including AI tools into the DMAIC framework helps to create a more cooperative environment, so improving the process.

During the Measure and Analyze stages, artificial intelligence (AI)-driven Data Integration combines and standardises several, real-time data sources. While Advanced Analytics give vital insights and early warning signs, Anomaly Detection, Predictive modelling, and Data Integration all help to complete Analyze and accurate Measure phase. The Improve phase support the main integrated hypothesis (H1), which holds that AI lets simpler bug detection and less variation, so improving quality assurance. AI-driven Prescriptive Analytics enhance data-driven decision-making across the Improve phase unlike more traditional methods of process improvement. Reinforcement learning algorithms and simulation models are applied to identify the optimal approaches to raise process efficiency while lowering cycle frequency and waste. This is consistent with the second hypothesis (H2), according to which the process will be more effective.

By means of Real-time Monitoring and Automated Alerts systems best for spotting and fixing process deviations, artificial intelligence (AI) enhances control. This raises the operational dependability. Reduced process variance and enhanced quality results point to the third hypothesis (H3) as supported. Applying AI-driven Data Integration, Real-time Data can be easily acquired and standardised from a variety of sources, such as sensor assessments, machine logs, and quality control reports, during the Measure and Analyze phases. Thanks to this integration, users can use comprehensive Anomaly Detection and Predictive Analytics tools, as well as identify process deviations and defects. Insights from Analytics decrease downtime, increase manufacturing line accuracy, and alert users to potential system failures in advance. That AI makes it easier to detect defects and reduces process variability, adding support to the first hypothesis (H1).

Fig. 3. The graphic presented illustrates the interrelationship among the DMAIC phases, AI tools, and the integrated hypotheses within a conceptual framework

Source: own research.

The conceptual framework of the DMAIC stage is supported by these integrations, corresponding AI components, and hypotheses.

The sequential DMAIC phases (Define, Measure, Analyze, Improve, Control) form the backbone of the process.

AI tools are integrated into specific phases:

Data Integration: Operates in the Measure phase to capture Real-time, heterogeneous data.

Advanced Analytics: Applied in the Measure, Analyze, and Improve phases to support Predictive, Prescriptive, and Anomaly Detection functions.

Real-time Monitoring: Implements control mechanisms in the Control phase with Automated Alerts.

The corresponding hypotheses are linked as follows:
H1: Is supported by AI-driven Analytics in the Measure/Analyze stages, asserting improved detection of defects and reduced variability.
H2: Is linked to the use of Prescriptive Analytics in the Improve phase to enhance process improvement.
H3: Is supported by Real-time Monitoring in the Control phase which leads to sustained operational stability.

Conclusion

The incorporation of AI technologies into the DMAIC framework has significantly enhanced our capacity to optimise the manufacturing process. A thorough study found that the phases of Measure and Analysis are better when AI brings together real-time data from different sources, like IoT sensors, equipment records, and quality assurance databases. The prompt identification of quality issues, enabled by Advanced Analytics like predictive modelling and outlier detection, has led to a decrease in process variability and defects. This method supports the hypothesis that AI can improve process consistency (H1) and assist in flaw detection.AI-driven Prescriptive Analytics has transformed conventional process redesign methodologies in the enhancement phase. Reinforcement learning systems and simulation models offer data-driven guidance for optimal process adjustments. The idea that Analytics powered by AI could speed up process improvement is supported by big drops in cycle times, waste, and overall production costs after getting analytical insights(H2). To keep the Control phase under constant supervision, we need to use real-time systems driven by AI. This ensures the process maintains consistency over time. Automated alerts and control systems facilitate prompt corrective actions, reducing rework and downtime. This control method supports the idea that monitoring systems that are powered by AI make processes more stable and improve the quality of compliance (H3). When AI is added to DMAIC, it creates a feedback loop that encourages continuous improvement and links big decisions to everyday tasks. This convergence improves the manufacturing process via data collection, analysis, process optimisation, and continuous control, resulting in enhanced product quality, reduced operational costs, and increased competitiveness in a dynamic industrial landscape. The paper does not discuss the possible negative effects of including AI in Lean Six Sigma approaches or offer thorough case studies or quantitative analyses to support the suggested hypotheses in different manufacturing sectors. Furthermore, not well investigated are the long-term consequences and sustainability of AI-enhanced DMAIC methods. These limitations suggest that more empirical research is necessary to support the theoretical hypotheses and investigate the pragmatic difficulties in applying AI-integrated DMAIC in actual manufacturing environments. Future research employing AI, combined with DMAIC methodologies, may improve process control, minimize errors, and increase overall manufacturing efficiency. These projects will enable businesses to maintain a competitive advantage in an increasingly artificial intelligence-driven industrial environment, advancing the next stage of manufacturing innovation. The continued application of artificial intelligence within the DMAIC framework necessitates continuous developments in these technologies to keep up with evolving customer requirements.

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