

SIX SIGMA IN THE DIGITAL AGE: INTEGRATION WITH ARTIFICIAL INTELLIGENCE AND BIG DATA FOR PROCESS IMPROVEMENT

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Abstract: This article investigates the integration of Six Sigma methodology with Artificial Intelligence (AI) and Big Data to optimize processes in the digital age. Six Sigma, developed in the 1980s, has established itself as a systematic approach to reducing variability and improving quality in industrial and service processes. However, with the rise of tools such as AI and Big Data, a new frontier for process optimization has opened up.

The study analyzes how the combination of these technologies allows for a reduction in analysis time, a decrease in manufacturing defects, an optimization of operational productivity, and a more sustainable approach to processes. Case studies are highlighted in industries such as soap, semiconductor, and textile manufacturing, where the application of AI and Big Data has shown significant results, such as a reduction in defects from 4.5% to 0.8% and optimization of resource consumption.

Despite the benefits, challenges such as high costs and lack of training in AI and Big Data are identified. The article concludes that the integration of these technologies with Six Sigma represents a significant evolution in process improvement, fostering innovation and competitiveness in the era of Industry 4.0. Investing in training and scalable tools is recommended to maximize the benefits of this integration.

Keywords: Six Sigma, DMAIC, Artificial Intelligence, Big Data, Predictive Quality Control, Industry 4.0, Machine Learning, Smart Manufacturing.

Abstract: This article investigates the integration of the Six Sigma methodology with Artificial Intelligence (AI) and Big Data to optimize processes in the digital era. Developed in the 1980s, Six Sigma has become a systematic approach to reducing variability and improving quality in industrial and service processes. However, with the rise of tools such as AI and Big Data, a new frontier for process optimization has emerged.

The study analyzes how the combination of these technologies enables a reduction in analysis time, a decrease in manufacturing defects, and an optimization of operational productivity, along with a more sustainable approach to processes. Case studies in industries such as soap manufacturing, semiconductors, and textiles are highlighted, demonstrating significant results from AI and Big Data applications, such as reducing defects from 4.5% to 0.8% and optimizing resource consumption.

Despite the benefits, challenges such as high costs and a lack of training in AI and Big Data are identified. The article concludes that integrating these technologies with Six Sigma represents a significant evolution in process improvement, fostering innovation and competitiveness in the Industry 4.0 era. Investing in training and scalable tools is recommended to maximize the benefits of this integration.

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INTRODUCTION

Nowadays, operational efficiency and continuous improvement have become important issues for organizations that want to maintain their competitive advantages in the digital environment. The Six Sigma methodology, developed in the 1980s by Motorola, has established itself as a systematic approach to reducing variability and improving quality in industrial and service processes (Navarro Albert et al., 2017). Its implementation is based on the DMAIC structure, consisting of five sequential phases (Define, Measure, Analyze, Improve, and Control), which allows operational problems to be addressed in a structured manner.

In recent years, the rapid development of advanced technological tools such as Artificial Intelligence (AI) and Big Data has transformed multiple industrial sectors. The combination of Machine Learning with Six Sigma in predictive maintenance strategies reduced equipment failure rates, improved Overall Equipment Effectiveness (OEE), and optimized process stability (C_p and C_{pk}) (Shivaramu, 2025). These advances have enabled companies to minimize downtime, reduce operating expenses, and raise production quality standards. However, the integration of AI and Big Data with Six Sigma still presents challenges, such as the lack of standardized models, adaptation to different industrial sectors, and resistance to organizational change (Malta et al., 2023). Despite advances in digitization and process improvement, there are still gaps in the literature regarding the application of AI and Big Data in real-time decision-making within the DMAIC cycle. While some studies have explored the combination of these technologies, their effective implementation remains a challenge due to the lack of standards, the handling of large volumes of data, and the need for more accurate predictive models (Antony et al., 2020).

General objective

The main objective of this article is to address the gaps in the literature regarding the application of AI and Big Data in Six Sigma, specifically in the real-time decision-making process within the DMAIC cycle. Despite advances in digitization, there are still limitations in the implementation of these technologies, such as the lack of standards, the management of large data sets, and the need for more accurate predictive models.

Specific objectives

- Conduct a literature review and analyze the impact of the integration of Artificial Intelligence (AI) and Big Data in each phase of the Six Sigma DMAIC cycle.
- Evaluate real-world case studies where the combination of Six Sigma, AI, and Big Data has been successfully implemented.
- Propose a conceptual framework that facilitates the integration of AI and Big Data in Six Sigma projects aimed at Industry 4.0.

Justification

The integration of Six Sigma with AI and Big Data represents an opportunity to improve and optimize operational performance and process quality in Industry 4.0. However, the lack of specialized research on its implementation limits its widespread adoption. This review will contribute to knowledge on the subject, providing a detailed analysis of its impact and facilitating future research on the convergence of these methodologies.

DEVELOPMENT

Fundamentals of Six Sigma

The Six Sigma method was developed in the 1980s by Motorola, led by engineer Mikel Harry. Its goal was to reduce variability in processes through data intelligence and continuous improvement, which led to its adoption in multiple industries. The result was optimal as it improved quality. Due to these results, the industrial sector began to develop new techniques to be more productive and continuously improve. The objective of the methodology is to increase process capacity in such a way that defects are reduced to a level that is imperceptible to the customer (Navarro Albert et al., 2017).

One of the most comprehensive definitions of Six Sigma, covering both its purpose and how it is applied. They define Six Sigma as a structured methodology that helps minimize

variability in organizational processes. To achieve this, it relies on experts in continuous improvement, follows a well-defined method, and uses performance metrics with the aim of achieving strategic goals (Prabhushankar et al., 2008).

DMAIC Methodology

DMAIC is the core methodology of Six Sigma, representing a systematic approach to process improvement that is implemented in a structured manner in organizations. This series of steps consists of defining the problem, measuring, analyzing, proposing improvements, and controlling the processes involved (Malta et al., 2023). We will explore the principles and stages of DMAIC and how it can be applied to achieve substantial improvements in process efficiency and quality. Figure 1 shows a representation of the DMAIC cycle and its main phases.



Figure 1. *Six Sigma methodology.*
Source: Own elaboration (2024).

Define:

In this first phase, it is essential to define the project's objectives and scope, prioritizing why the project is being carried out, what the expected benefits will be, and what the metrics for success will be. It is extremely important that senior management approve the project and support its development (Gutiérrez Pulido & Vara Salazar, 2013).

Measure:

In this second phase, it is essential to gain a more detailed and accurate understanding of the magnitude of the problem or situation that the project seeks to resolve. To achieve this, the process is defined in

in greater detail, analyzing operational flows, decision nodes, and execution variables. In addition, specific indicators are established to objectively evaluate the success of the project. At this stage, specific tools are used to analyze and improve processes. Some of the most useful tools include:

- Detailed process mapping
- R&R (Repeatability and Reproducibility) analysis
- Applied statistical fundamentals
- Process capability analysis
- FMEA: Structured method for anticipating and mitigating potential failures
- Six Sigma metrics

These tools enable the evaluation and improvement of process efficiency and quality (Gutiérrez Pulido & Vara Salazar, 2013).

Analyze:

Third phase: this is where it is important to identify the root cause of the problem, verify and confirm the causes with data, and include all variables that are relevant and could potentially influence the problem. In this phase, a variety of tools are used to analyze and solve problems. Some of the most common tools include:

- Creativity techniques such as brainstorming.
- Causal analysis tools such as the Ishikawa diagram (fishbone diagram) and the 5 Whys technique for identifying root causes.
- Data analysis methods, including second-level Pareto charts and scatter plots.
- Control and monitoring tools such as control charts.
- Mapping and design techniques such as process mapping and quality function deployment.
- Statistical methods such as design of experiments and hypothesis testing.

These tools enable problems to be identified and resolved effectively and efficiently (Gutiérrez Pulido & Vara Salazar, 2013).

Improve:

In this phase, solutions aimed at the root causes of the problem must be proposed and implemented. Its main purpose is to resolve the underlying factors that cause the problem, rather than just treating its symptoms. To

achieve this, it is important to generate several solution options. Various solutions should be explored through brainstorming, creative methods, and experimentation, ensuring that the most effective alternative is chosen.

Once several solution options have been generated, it is important to evaluate them objectively using a priority matrix. This matrix allows solutions to be weighted and ranked according to different criteria, such as cost, ease of implementation, and benefits. The solution with the highest score will be the best option according to the established criteria (Gutiérrez Pulido & Vara Salazar, 2013).

Control:

The main idea of this stage is to control and maintain the improvements achieved in a process. Once the desired improvements have been achieved, it is essential to design a system that maintains and consolidates the changes made. This involves institutionalizing and generalizing the improvements, which may require adaptation and taking into account all participants in the process. The objective is to periodically review that the improvements are maintained over time and are not lost. To achieve this, it is necessary to follow a control procedure that prevents the recurrence of problems, keeps the process in good shape, and encourages continuous improvement.

To ensure the sustainability of improvements, control processes must be established at three different fundamental levels: during the process, documentation, and monitoring. This will maintain the efficiency and quality of the process, guarantee the accuracy and timeliness of documentation, and enable continuous monitoring of process performance (Gutiérrez Pulido & Vara Salazar, 2013).

Limitations and trends of Six Sigma

Six Sigma has been a key tool for many companies, helping to reduce costs and defects in their processes. However, success is not always guaranteed. It is estimated that 62% of Six Sigma initiatives have failed. Often, these projects start with good momentum but lose steam over time, which demotivates organizations and causes them to revert to their old practices (Albliwi et al., 2014). In the healthcare sector, for example, more than half of companies have no real intention of implementing Six Sigma. Furthermore, some experts warn that focusing too much on efficiency can affect a company's long-term growth (Antony et al., 2020).

Today, with the advent of the Fourth Industrial Revolution, companies generate enormous volumes of data that can be leveraged to make better decisions based on analysis, but this is becoming increasingly complex. For Six Sigma to remain an effective methodology, it is key to

to use this data intelligently. It is also important to incorporate environmental factors into processes and find solutions that allow small and medium-sized enterprises to adopt this methodology in a more accessible and effective way (Antony et al., 2020).

Artificial Intelligence and Six Sigma

For more than 60 years, scientists and engineers have been working continuously on the development of artificial intelligence (AI). The main purpose is based on the idea that machines created by humans can not only perform mechanical and/or repetitive tasks, but also develop intelligence comparable to that of humans. AI has become integrated into our daily lives, taking on key roles in industry, healthcare, transportation, and education.

AI has been defined in various ways over time. For example, in the famous Turing Test, it is proposed that a machine can be considered intelligent if it is capable of interacting with humans through electronic means without them realizing that they are not talking to another person. Marvin Minsky, a key figure in the development of AI, described it as the power of automated devices to perform specific actions or functions that, if performed by humans, would require intelligence. Despite these differences in definitions, there is a consensus that AI refers to a set of technological tools and applications designed to complement and enhance human intelligence capabilities (Jiang et al., 2022).

The keys to AI in industry lie in machine learning (ML), which can recognize patterns in linear and non-linear data, unstructured data (images or text), has fast calculation speeds, and high interpretability, making it understandable to humans. Often, the relationship between input parameters (e.g., temperature, pressure, speed) and output parameters (e.g., product quality) is very complex and not fully understood, even under simplified conditions. Therefore, this relationship is unknown due to extremely nonlinear correlations (Kim et al., 2022).

This is where AI comes into play, especially deep learning (DL), which is a part of machine learning (ML). Deep learning is beginning to replace traditional data analysis techniques because it is capable of:

- Recognize elaborate configurations in training data sets.

In a factory, the relationship between temperature, pressure, and product quality can be very complicated and may not follow a simple mathematical formula.

- Identify various forms of complex data structures, such as videos, documents, and recordings.

Deep learning (DL) implements artificial neural networks (ANNs) with multiple layers to find nonlinear relationships and complex patterns. These networks are particularly good at working with complex structured data, such as text, images, or sound. The advantage of using these tools is quality assurance. Likewise, both ML and DL offer tools to improve processes through data-based quality analysis, which guides us toward predictive quality (Tercan & Meisen, 2022).

These AI tools are trained to improve quality by learning from data using machine learning and deep learning techniques (Sood & Dhull, 2024). The basis for training any AI model is data. To improve quality, this data often includes historical production data, equipment sensor readings, quality control records, customer feedback, and information about process parameters (Bukhari & Akhtar, 2024; Sood & Dhull, 2024). This data must be collected, cleaned, and prepared in a format suitable for AI algorithms (Parmar, 2022).

The most common techniques for solving the quality problem are chosen from among different AI algorithms:

Machine learning (ML):

These algorithms allow AI to learn from data and improve accuracy over time without explicit programming (Sood & Dhull, 2024).

- Clustering and dimensionality reduction: This is used to analyze large data sets and automatically find inefficiencies or uncover hidden problems (Sood & Dhull, 2024).
- Decision trees and logistic regression: These are used for predictive modeling, such as forecasting the probability of a defect occurring based on historical data (Bukhari et al., 2024).
- Support vector machines (SVM): These are used to improve root cause identification (Bukhari et al., 2024).
- Association rule learning (Apriori algorithm): helps detect hidden patterns and trends in data (Bukhari et al., 2024).

- Time series forecasting (e.g., ARIMA, LSTM): provides predictive information to anticipate future process inefficiencies (Bukhari et al., 2024).
- Reinforcement learning: can be used for continuous process optimization by exploring a wide range of solutions and selecting the most effective ones (Bukhari et al., 2024).

Deep learning (DL):

This is a specialized branch of machine learning that uses neural architectures, excelling in applications such as visual identification and sound processing, as well as sentiment analysis of text data (natural language processing technique). Some examples include:

- Transformers and RNNs (recurrent neural networks): these are used in the definition phase to process customer perceptions, comments, and ratings. To identify recurring complaints.
- Deep neural networks: these can be trained for predictive modeling in the control phase, such as to forecast equipment failures (Sood & Dhull, 2024).

Model training:

Once the data is prepared and an algorithm is selected, the AI model is trained using this data. This involves feeding the data into the algorithm, which then learns the hidden relationships and patterns. The model's performance is evaluated on a separate portion of the data (the validation set), and the model parameters are adjusted to improve its accuracy and generalization ability (Bukhari & Akhtar, 2024).

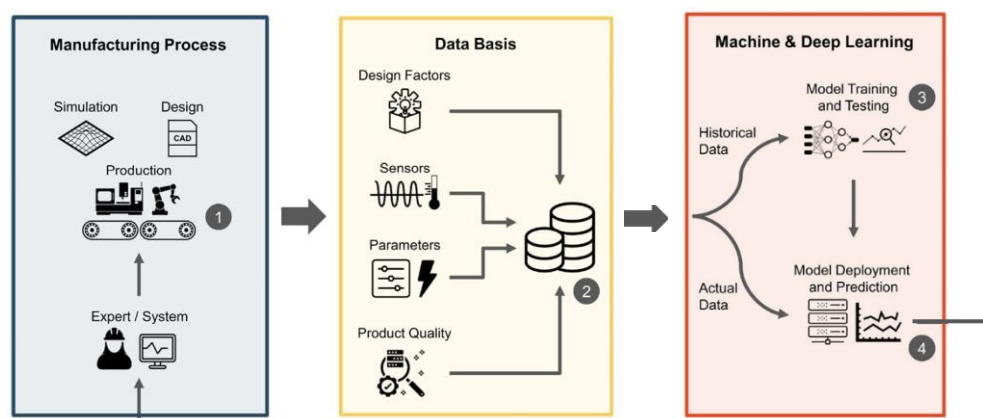


Figure 2. Artificial Intelligence and Six Sigma.
Source: Predictive Quality Approach (Tercan & Meisen, 2022).

Figure 2 shows a graph of the predictive quality approach:

1. Manufacturing process
2. Relevant process and quality data are collected.
3. This data is used as the basis for training a machine learning model.
4. The trained model is used to make quality estimates to support decision-making.

Studies show that predictive quality is viable, as demonstrated in a car body parts manufacturing process, specifically in the stamping process. In this way, more than 94% of process failures are predicted (Meyes et al., 2019).

Big data

Big data refers to extremely large and complex data sets that cannot be processed with traditional analysis tools. Since 2016, the volume of information generated and stored has been multiplying, thanks to technological advances and lower costs associated with storing this data. Big data is transforming the way knowledge is extracted, enabling the discovery of hidden patterns and decision-making. However, its analysis requires advanced statistical methods, efficient computational tools, and architectures designed to handle its complexity (Fan et al., 2014).

Big data processing in industrial environments not only identifies faults and optimizes processes, but also consolidates itself as a facilitator in data-backed strategic decisions. Tools such as machine learning and deep learning are being used to extract complex patterns from large volumes of unstructured data, such as images, text, and sound (Khan et al., 2017). In industrial automation, data is acquired through SCADA systems, and signals from sensors, PLCs, and actuators are transformed into visual signals that can be interpreted by users. All this information must be collected and integrated into a data model.

The big data analysis techniques that can be adapted and integrated into the Six Sigma methodology in the DMAIC phases are as follows (Al-Rifai, 2025; Baiochi et al., 2025).

Measure: Time series analysis is used to analyze historical data trends and, in this phase, allows patterns to be detected and potential problems to be located.

Analyze: Data mining allows hidden relationships to be discovered in large amounts of data sets, thus directly supporting the identification of root causes of defects.

Control: The implementation of a monitoring system that collects information about a process, such as data on temperature, pressure, and vibrations. The result is a prescriptive analysis. This type of application prevents defects and improves process stability through early fault detection.

Big data, Artificial Intelligence, and Six Sigma

The combination of intelligent algorithms (AI) and the analysis of large volumes of information (big data) has been applied in the various phases of the Six Sigma DMAIC methodology to improve process optimization and predictive quality control (Bukhari et al., 2024; Sood & Dhull, 2024). Below is a detailed description of how these technologies have been integrated into each phase:

Define:

AI can help identify problems and gain insights about customers. This may involve using machine learning models to analyze customer feedback, identify key performance indicators (KPIs), and define project objectives more accurately (Bukhari et al., 2024). AI can process large data sets to detect critical areas for improvement that may not be obvious through traditional analysis (Bukhari & Akhtar, 2024).

Measure:

AI tools can be used to analyze historical data and identify factors that contribute significantly to quality issues (Bukhari et al., 2024). Real-time information gathering from multiple sources, such as IoT devices and ERP (Enterprise Resource Planning) business management software, coupled with AI-driven anomaly detection, enables more accurate and timely insights into process metrics. AI can continuously monitor processes, providing up-to-date information for measurement (Bukhari & Akhtar, 2024).

Analyze: Machine learning algorithms are used to identify root causes. Deep learning is applied to analyze unstructured data, such as images or videos, and detect defects in products (Bukhari & Akhtar, 2024).

At this stage, AI has the primary responsibility for identifying the causes of problems. AI-based analysis, such as machine learning models, can detect key factors that contribute to defects.

These models can identify hidden relationships between production variables and quality outcomes. AI and big data can automatically analyze large volumes of data, recognize complex patterns, and perform predictive analytics to detect the main factors that generate waste and failures. In addition, root cause analysis can be complemented with AI to provide more detailed information (Bukhari et al., 2024).

Improve: AI facilitates the design, testing, and implementation of solutions. Predictive AI models can anticipate the likelihood of defects occurring in specific batches using historical data, allowing for early identification and review (Bukhari et al., 2024). AI digital twins enable the simulation of physical processes to test potential changes without affecting actual operations. Reinforcement learning and evolutionary algorithms can be used to optimize processes by exploring various solutions and choosing the most effective ones. For example, neural networks can improve production scheduling and supply chain logistics (Sood & Dhull, 2024).

Monitor: AI is essential for maintaining improvements and preventing problems from recurring. Statistical Process Control (SPC) charts can be enhanced with AI for anomaly detection, allowing systems to recognize when performance is declining and take early action (Bukhari & Akhtar, 2024). AI-based alert systems can monitor the production process in real time and identify any deviations (Bukhari et al., 2024). AI can also create feedback loops where process parameters are adjusted based on real-time conditions. AI-driven preventive maintenance algorithms can track equipment status to prevent downtime and improve process stability (Bukhari & Akhtar, 2024).

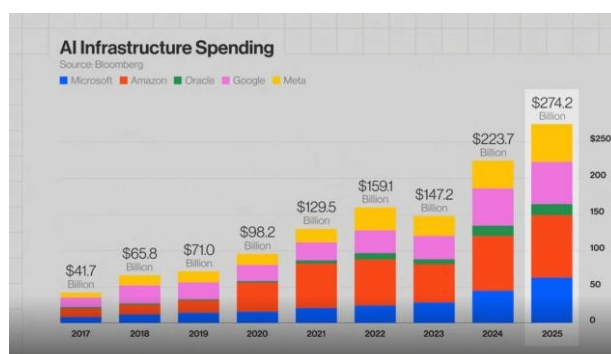


Figure 3. AI growth.

Source: Spending on Artificial Intelligence Infrastructure (Bloomberg, 2024).

In summary, artificial intelligence acts as a key support throughout the DMAIC cycle, identifying and resolving problems, providing deeper analysis, supporting the development of more optimal solutions, and contributing to sustainability through continuous monitoring and control (Bukhari & Akhtar, 2024; Sood & Dhull, 2024). This integration is focused on Industry 4.0 principles, leveraging real-time data and intelligent systems to optimize processes and improve predictive quality control.

In recent years, investment in artificial intelligence (AI) infrastructure has grown exponentially, driven by large technology companies. Spending on AI infrastructure is projected to double between 2023 and 2025, reaching \$274 billion (Figure 3). This trend suggests that artificial intelligence will be a key pillar in the digital transformation of industry.

Traditional Six Sigma vs. Six Sigma with AI and Big Data.

Traditionally, Six Sigma relies on statistical tools and quality management principles applied to collected data to identify and eliminate sources of error and inefficiency (Bukhari & Akhtar, 2024). The measurement phase often involves collecting and interpreting physical data, which can be time-consuming and prone to human error. The analysis phase uses statistical methods to find the root causes of problems, which can be challenging with large data sets (Parmar, 2022). The control phase focuses on monitoring process performance using tools such as statistical process control (SPC) charts to ensure consistency (Sood & Dhull, 2024).

Six Sigma integrated with Artificial Intelligence (AI) and Big Data represents an evolution that significantly improves the capabilities and effectiveness of the traditional methodology (Bukhari et al., 2024; Bukhari & Akhtar, 2024). Big Data provides large amounts of real-time data from various sources, including IoT devices and business management systems (Diaz, 2024). AI, particularly machine learning and deep learning, offers advanced tools to analyze this data, predict outcomes, and automate actions throughout the DMAIC cycle.

The key benefits of integration are:

- Greater speed and accuracy in problem detection (Bukhari & Akhtar, 2024; Sood & Dhull, 2024).

- Predictive capabilities to reduce defects and waste (Bukhari et al., 2024).
- Scalability and continuous monitoring across the organization (Sood & Dhull, 2024).
- Resource optimization and sustainability through advanced analytics (Bukhari & Akhtar, 2024; Diaz, 2024).

In conclusion, while traditional Six Sigma methodology provides a solid framework for process improvement, the integration of AI and Big Data revolutionizes it by providing powerful tools to manage large data sets, gain deeper insights, predict future outcomes, and automate important steps in the DMAIC cycle. This translates into faster, more efficient, accurate, and sustainable quality improvements compared to the traditional approach.

Six Sigma and its traditional approach differ greatly when applied with AI. When applied simultaneously, there is a significant reduction in defects and improved process efficiency. Figure 4 shows how the implementation of AI has increased the effectiveness of predictive maintenance, achieving a reduction in costs and downtime.

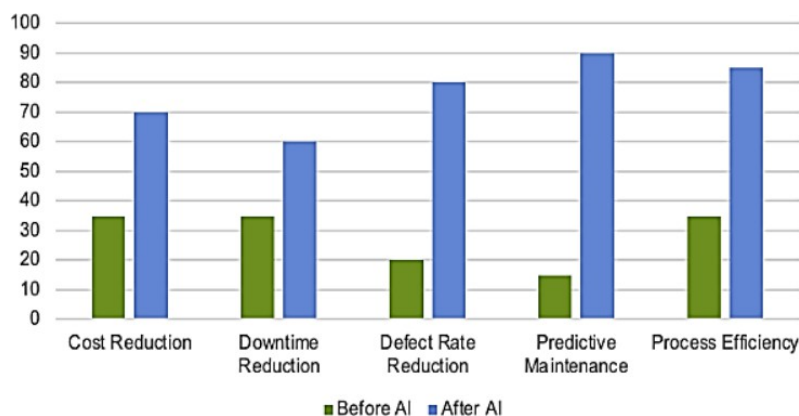


Figure 4. *Traditional Six Sigma vs. Six Sigma with AI and Big Data.*

Source: Comparison of the impact of Artificial Intelligence implementation (Sood & Dhull, 2024).

Case Studies and Practical Applications Soap Industry

Shakir Bukhari's 2024 study is a case of integrating Six Sigma and AI to improve quality and reduce waste in a soap manufacturing industry.

Problem: Quality defects and high material waste.

Solution: Six Sigma was applied with AI (machine learning) tools to identify causes of defects and predict failures.

Results: Reduction from 4.5% to 0.8% in defects and 22% less waste (Bukhari et al., 2024).

Predictive Maintenance with TensorFlow

Study by Anitej Chander Sood 1 and Konika Singh Dhull 2024, reviewed how TensorFlow, an AI tool, improved their maintenance practices.

Problem: Downtime due to machine failures.

Solution: Use of TensorFlow in the Six Sigma DMAIC framework to predict failures by detailed review of sensor data.

Results: Proactive maintenance and reduction of unplanned downtime.

Supply Chain Optimization

Study by Anitej Chander Sood 1 and Konika Singh Dhull 2024 reviewed how an organization addressed AI technologies in the Six Sigma DMAIC architecture to address difficulties in its supply chain, including delayed shipments and inefficient warehouse utilization.

Problem: Shipping delays and inefficient warehouse utilization.

Solution: Integration of AI to analyze and optimize supply chain data instantly.

Results: Improvements in on-time delivery and inventory management.

Semiconductor Manufacturing

Tarun Parmar's 2022 study examined how a semiconductor factory maintained low yields.

Problem: Low yields on new chip designs.

Solution: Merging Six Sigma, statistical models, and AI to optimize big data processing in industrial environments.

Results: 15% increase in production yield.

Textile Manufacturing

Study by Rahaman, Md Saidur reviewed the manufacturer's case studies.

Problem: Process inefficiencies and high resource consumption.

Solution: Implementation of IoT and AI together with Lean Manufacturing and Six Sigma to optimize processes.

Results: 20% reduction in water consumption, 12% reduction in energy consumption, and 18% reduction in carbon emissions.

DISCUSSION AND ANALYSIS OF RESULTS

1. Reduction in Analysis Time

The implementation of AI tools, such as machine learning and deep learning, enabled a 50% reduction in analysis time. This facilitates faster and more efficient decision-making, aligning with the goal of optimizing processes and improving operational efficiency.

2. Decrease in Manufacturing Defects

AI-based predictive analytics proved effective in reducing manufacturing defects. In the soap industry, the defect rate decreased from 4.5% to 0.8%, significantly improving product quality and reducing associated costs.

3. Improved Operational Efficiency

The automation of repetitive tasks using AI improved operational efficiency. For example, predictive maintenance with TensorFlow reduced downtime and optimized resources, generating savings in operating costs.

4. Predictive Capability and Sustainability

The integration of AI and Big Data made it possible to anticipate failures and reduce downtime. In textile manufacturing, real-time monitoring reduced water consumption by 20%, energy use by 12%, and carbon emissions by 18%, promoting sustainability.

5. Limitations and Challenges

Despite the benefits, barriers such as high costs and lack of training in AI, Big Data, and Six Sigma were identified. This highlights the need to invest in training to maximize the benefits of this integration.

When comparing the traditional Six Sigma approach with the one integrated with Artificial Intelligence and Big Data, significant improvements are evident in each phase of the DMAIC cycle. In the Define phase, AI facilitates the rapid and accurate identification of critical issues through advanced analysis of large data sets from customer feedback and internal processes, something that would require much more time and resources manually. During the Measure phase, integration with IoT and predictive analytics enables real-time data collection and monitoring, substantially improving the accuracy and speed of measurements compared to the traditional method based on periodic sampling. The Analyze phase benefits greatly from the use of machine learning algorithms to discover complex patterns and root causes in massive data sets, far exceeding the limitations of conventional statistical methods.

Likewise, in the Improve phase, AI-powered predictive models and digital twins enable the evaluation of multiple potential scenarios in a way that

virtual and anticipated, optimizing resources and reducing operational risks that the traditional method, based mainly on trial and error or physical pilot tests, cannot match in efficiency.

Finally, in the Control phase, intelligent systems facilitate proactive monitoring and automation of process control through early warnings and predictive maintenance, significantly reducing the risk of setbacks or loss of improvements, compared to the manual or reactive systems traditionally used in Six Sigma.

CONCLUSIONS

The integration of Artificial Intelligence (AI) and Big Data with the Six Sigma strategy represents an important evolution in process improvement, enabling organizations to achieve higher levels of efficiency, quality, and sustainability.

However, the implementation of these technologies is not without challenges. High infrastructure costs and lack of training are barriers that must be overcome to reap the benefits of this integration. Organizations are advised to invest in training.

In conclusion, combining Six Sigma with AI and Big Data not only improves process quality and efficiency but also fosters innovation and sustainability, positioning itself as a key strategy for competitiveness in the Industry 4.0 era. Future research could explore the application of these technological tools in small and medium-sized enterprises (SMEs) and the use of digital twins for process simulation and optimization.

Unlike the traditional approach, which relies heavily on manual statistical analysis and human supervision, integration with AI and Big Data enables continuous automated, predictive, and scalable improvement. This capability transforms Six Sigma into a key tool for addressing the dynamic challenges of Industry 4.0.

FUTURE WORK

In the future, a broad field of work is expected, focused on the development of AI models that integrate Six Sigma structural logic with machine learning algorithms and big data analytics systems. This field will include:

- Automation of the DMAIC cycle using AI systems capable of executing complete phases (define, measure, analyze, improve, and control) with minimal human intervention.
- Development of integrated digital platforms (based on IoT, ERP, and smart sensors) that collect, analyze, and optimize data in real time in industrial environments.

- Implementation of digital twins and advanced simulations to test process changes before their physical execution.

This working study requires collaboration between multidisciplinary process, data, and artificial intelligence engineers, as well as ongoing investment in professional training and technological development.

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