Intellecta : Journal of Artificial Intelligence
Volume. 1 Issue 1 December 2025
Page No: 31-46

AI-Driven Enhancements across Mechanical Product Engineering Lifecycle

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Received : October 12, 2025
Accepted : November 13, 2025
Published : December 30, 2025

Citation: Shaikh, F, A., & Panta, S. (2025). AI-Driven Enhancements across Mechanical Product Engineering Lifecycle. Intellecta : Journal of Artificial Intelligence, 1(1), 31-46

ABSTRACT: Artificial Intelligence (AI) has emerged as a transformative force in the field of mechanical engineering, influencing key stages of the product engineering lifecycle, including design, manufacturing, and quality control. This study explores the integration of AI technologies into traditional engineering practices, focusing on how AI enhances efficiency, accuracy, and decision making. Using a case study of plastic bottle production, the research compares traditional methods with AI-driven approaches in terms of time efficiency and process optimization. The findings reveal that AI significantly reduces design and manufacturing time, improves precision in quality control, and minimizes manual intervention. In the design phase, AI algorithms assist in generating optimized design alternatives based on historical data, while in manufacturing, predictive models streamline planning and machine setup. Quality control is notably improved through real-time monitoring and AI-based fault detection systems. These results demonstrate the potential of AI to modernize mechanical engineering workflows, offering a more intelligent, efficient, and cost-effective approach to product development. The study concludes that AI integration is not only a technological advancement but also a strategic necessity for improving productivity and maintaining competitiveness in a rapidly evolving industrial landscape.

Keywords: Artificial Intelligence, AI Integrated Mechanical Design, AI Integrated Manufacturing, AI Integrated Quality Control.

INTRODUCTION

Artificial Intelligence (AI) is transforming traditional mechanical engineering approaches by revolutionizing conventional methods of design, manufacturing, and quality control. One such evident case is GE Aviation that has incorporated AI-based predictive analytics in its jet engine production, allowing real-time monitoring and significantly minimizing unplanned downtime while increasing engine reliability (Fox, 1986). Examples like these present how AI turns reactive systems into predictive and optimized processes. AI technologies enable engineers to review huge data sets, speed up the optimization of designs, and make informed decisions based on data at each step of the product lifecycle. Specifically, AI joined with CAD tools makes generative design and performance prediction possible, while intelligent manufacturing solutions simplify planning, setup, and execution. In the same way, AI-fueled quality systems identify defects in real-time and decrease inspection time considerably. This work investigates these developments and offers a comparative case study of plastic product production, illustrating how AI-based techniques enhance productivity, precision, and efficiency at all stages of engineering and significantly reducing the cycle time.

METHOD

Traditional Product Design Methodoly (Cad Based)

Traditional design process is a structured, methodical way of bringing ideas from conceptual into workable mechanical systems. Being an iterative process, each stage builds upon information provided by previous stages to refine and possibly optimize the design. Ullman et al., (1988), it generally commences with the definition of the problem, where the objectives, constraints, and the requirements of the design are clearly defined and outlined. During this stage, the extent of the problem is understood, including what functionality the product should offer and limitations due to cost, materials, or manufacturing processes. The following stage is the conceptual design phase, which addresses the generation of various possible and feasible solutions(Perera et al., 2019). Designers go through various design alternatives by brainstorming, sketching, and preliminary analysis(Hassan & Ayad, 2022). This stage is all about creativity and innovation in finding the most promising and acceptable concept(Santana et al., 2017). Once a concept has been chosen, it is then refined into a more concrete form through the embodiment design stage. Designers will choose components, materials, and dimensions, and then create detailed drawings and specifications (Carvalho et al., 2021). By (Otey et al., 2018), this stage bridges the gap between abstract concepts and tangible design parameters. According to detailed design is a stage where refinement of design takes place by considering tolerances, material specifications, and manufacturing processes. According to detailed drawings and computer-aided design models are produced that are complete in every respect for the final product. Throughout the design process, analysis and simulation tools are employed to evaluate the design's performance. This includes structural analysis, thermal analysis, and dynamic simulations, which help identify potential weaknesses or areas for improvement. Prototyping and testing are crucial for validating the design and uncovering unforeseen issues. Physical prototypes are tested under realistic operating conditions to provide feedback for further refinement (Chen et al., 2020). Finally, the manufacturing and assembly stage focuses on efficient production, considering factors such as cost, quality, and lead time.

Limitation of Traditional Design Process

1. Data Utilization: Traditional Design methods struggle to work with large historical data and are significantly time consuming, while AI can efficiently processes and learns from huge amounts of data

2. Decision-Making: Traditional Design approaches are more time consuming, while AI uses data-driven approaches making the process quicker and reliable
3. Innovation: Traditional designs are limited by human imagination & collaboration; AI looks for out-of-the-box and innovative solutions.
4. Cost-Effective: Cost-Effective: Traditional methods are resource heavy, while AI optimizes resources, reducing costs.

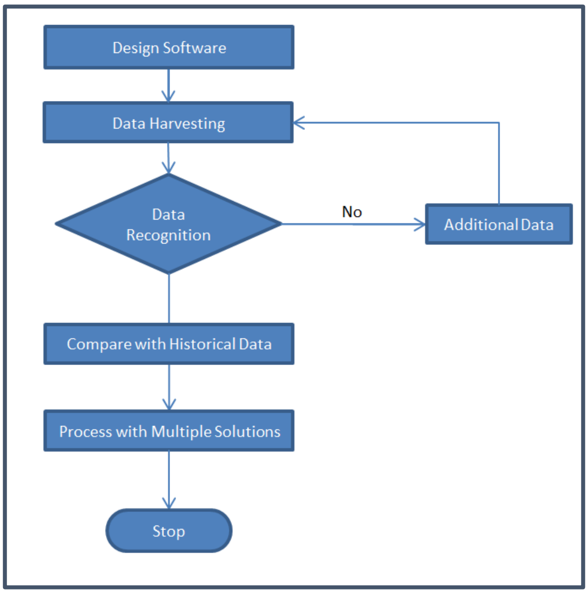
A.I Integration Into Product Design (A.I Based Cad)

The first phase in Mechanical Engineering is the Product Design Phase (Concept Design to Final Design). In this respect, AI algorithms and historical data-driven approaches may represent a revolutionary approach in comparison to traditional methodologies in Mechanical Design. While in the traditional methodologies, the designer used to spend a major portion of the time defining the design parameters-material selection, load-bearing capacity, GD&T, etc.-where engineers manually create and refine design solutions(Gero & Yu, 2020), AI integration in Mechanical design is based on AI algorithms and machine learning methodologies for automatic concept/ calculations of design parameters and constraints using historical data and computer intelligence in decision-making ability (Jiao & Alavi, 2021; Zhang et al., 2021). This approach, therefore, allows the investigation of very large design spaces and solutions which may be hard to intuit or even be feasible by manual processes and in turn provides the best possible solution's in most effectively and efficiently (Rao & Dutta, 2018).

Product designing using A.I. begins with requirement definition, Once the engineer define the required data then AI analyze the data to historical data from past designs/Cad models, geometrical constraints (GD&T) by machine learning approach from previous design calculations and identification of the design problem (Ahmed & Shaikh, 2022a; Sobester & Forrester, 2008) i.e., the design requirements, constraints, and needed parameters such as desired material properties, bearing load conditions, environmental factors, manufacturing methods and cost. AI algorithms will use this information to come up with a variety of options based on historical data. These AI-based algorithms can use methods such as advanced computing or high-performance computing (HPC), whereby design alternatives are iteratively refined based on performance criteria. Figure 1 shows a sample of the AI-based design architecture. For this to happen, the process should consist of a few key steps for integrating AI into Product Design (AI-Based CAD). By incorporating AI at each stage—data harvesting, smart analysis, optimization, and design generation—the system can automatically learn from vast engineering datasets to generate viable design solutions. Unlike traditional methods, which rely heavily on human iteration and limited exploration, AI systems can evaluate thousands of possibilities quickly and identify optimal solutions that meet predefined performance and cost targets. This significantly reduces design time, increases innovation potential, and minimizes the risk of design flaws early in the process. Such AI-driven simulation pipelines enable intelligent mechanical design far beyond manual capabilities (Bappy & Ahmed, 2023; Cagan & McComb, 2019).

- Data Harvesting: The design requirements will be defined manually by the engineer in the AI based model & the A.I algorithm will compare the given data from various historical data of success and failures.
- Smart Data Analysis: Through the A.I based algorithms and machine intelligence, the integrated cad software will then suggest the best suiting solutions from its history & also provide the solutions to create many design alternatives by modifying and combining various design possibilities, configurations & parameters.
- Optimization: Each of the designs may vary in the required parameters and iterative approach to arrive at the final model based on operational criteria such as availability, cost, strength, and manufacturability.
- Selection: Designers can then review the generated A.I designs and select the most desired solution based on practical considerations and additional refinements if required.
- Design Generation: Engineers can then generate the final design and modify its parameters as per the requirement.

Figure 1. Flow chart of A.I based design architecture



Comparison (AI integrated vs traditional design approach)

Table 1.Results of time consumption between A.I & traditional approach for design

Sl. No	Process	Traditional	AI Integrated
1	Concept Design	1 day - Defining design parameters, material selection, design & drafting	0.5 day - AI generated options for design parameters, material selection, concept design and drafting
2	Actual Design	2 days- Design manually	0.5 day - Use AI-based suggestions/models and modify according to the requirements

From Table 1 we can see that by Integrating AI into the design process (for example like ChtGPT integrated with CAD Software) greatly boosts efficiency, cutting total design time by approximately 50% while also encouraging creativity and best possible results.

Benefits of Integrating A.I Into Mechanical Design

- Better Efficiency and Optimization: By analysing a large historical design dataset, A.I design will help produce accurate solutions that may be time-consuming and prone to errors through traditional design practices. The result is more creative and cost-effective design solutions that can push the boundaries of required output.
- Improved Accuracy and Better Performance: AI can improve the accuracy of design calculations and results by analysing massive historical datasets and complex Algorithm patterns that may be missed by human approach . This shall bring improved accuracy, cost-effectiveness, and significant reduction in human efforts and expertise required to perform the job.
- Less Cycle Time: Automation in design process and evaluation reduces the manual efforts required towards researching and designing a particular component

Traditional Product Manufacturing

The manufacturing process involves processes such as shaping, casting, machining, joining and finishing transforming physical materials into final products in sequential steps using high-tech machines. These processes usually require high setup costs and are less flexible than modern technologies. Describes the optimization of efficiency, which aims to maximize output over time and minimize downtime and prioritizes Good work (Ali et al., 2016a). Manufacturing project management manages these processes to ensure completion time and allocate resources. In an environment where sellers and buyers are interconnected, factors such as rapid price formation, unreliable machines, spare parts, and remanufacturing for each order cause high workload. (Staiger & Voigt, 2024) Cost models usually estimate costs based on two factors, material costs and labor costs, while automation processes often require models that take into account investment costs and debt management. According to Dahotre & Harimkar, (2008) in specialized machinery manufacturing companies, techno-economic calculations for new product innovations include comparing designs and failure rates with existing products. Analyzing large data sets of previously created products. In general, the time and effort required to analyze historical production data for similarity is time-consuming and relies on human expertise.

Limitation of Traditional Mfg. Process

- Higher operational cost: Manual processes require more labor, and inefficient use of resources leads to increased expenses in terms of energy consumption, materials, and waste
- Limited data utilization: Traditional methods struggle to analyze large volumes of production data, preventing manufacturers from identifying trends, optimizing processes, and making data-driven decisions.

- Reduced competitiveness: Manufacturers without AI struggle to match the speed, efficiency, and cost-effectiveness of competitors who leverage smart technologies for innovation and growth.

A.I Integration Into Product Manufacturing (Smart Production)

The integration of AI into traditional manufacturing practices would make the sector very advanced and innovative. In a modern manufacturing milieu, AI can be employed on every front-from machine and tool setup to producing components and ensuring quality control-thus markedly improving reliability, efficiency, and operational costs. As an example, machine learning algorithms can analyze the historical data from past manufactured batches, evaluate real-time information from in-process production lines, and identify chances for flaws in active production. On top of that, AI-driven analytics may reduce the time required for the quality assurance process by utilizing data from sensor's and evaluating both historical and current design information to reduce risks with real-time production variability. These advantages of integrating AI into manufacturing exceed just cost reduction or lower levels of human effort; they also involve precision in product quality and production, which previously was only aspired to, thus opening the way to a marked improvement in customer satisfaction (Chen et al., 2020a). All of these improvements put together will help in realizing the true potential of AI in manufacturing. Figure 2 shows an example of the process architecture: The point is that AI in manufacturing has dramatically improved productivity, quality, and decision-making powers. Schedules of production are easier to handle by the manufacturer with the aid of machine-learning algorithms. AI helps in real-time processing and analysis for preventive maintenance, minimizing the occurrence of failures in processes and equipment, along with reducing maintenance costs. These AI-based algorithms can use methods such as Anomaly Detection / Machine Learning /high-performance computing (HPC)/ Convolutional Neural Networks (CNN) / Decision Trees which in turn will manufactures to quickly setup/alter the machine parameters for the production line (Kulynych et al., 2024).

Figure 2. Flow chart of A.I based manufacturing architecture

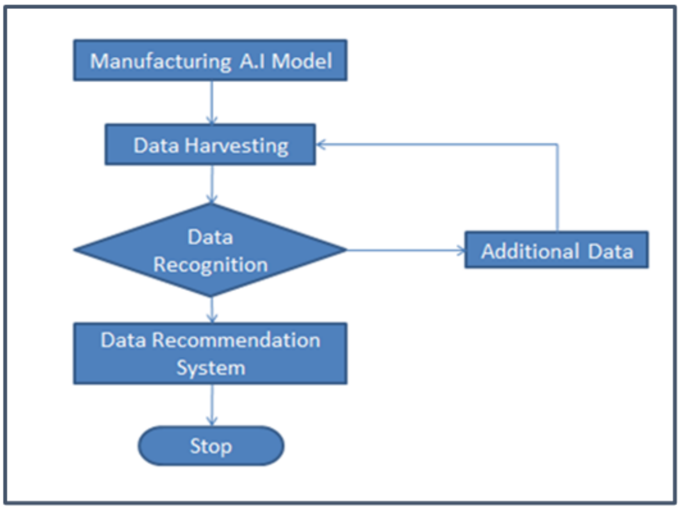


Figure 2. shows a sample of the A.I based manufacturing process architecture. For this to happen, the process should consist of the following key steps:

- Data Harvesting: The manufacturer requirements, manufacturing drawings will be manually defined by the engineer in the AI based manufacturing monitoring model & the A.I algorithm will compare the given data from various historical data of success and failures.
- Live Data collection & Data Analysis: Through the A.I based algorithms and machine intelligence; the integrated monitoring software will then compare the historical data against the live data and provide the suggestion to alter various required machine parameters to meet the actual requirement.
- Recommendation System: The A.I based recommendation system will provide the suggestions to alter in the current Process based on the data from past manufactured batch, Manufacturing drawings and current parameters results.

Comparison (AI integrated vs Traditional Manufacturing Approach)

Let us take a small example of manufacturing a plastic bottle

Table 2.Results of time consumption between A.I & traditional approach for mfg. process

Sl. No.	Process	Traditional Method	AI-Integrated Approach
1	Planning	Takes around 3 days with multiple iterations and resource planning efforts	Takes 0.5 day with AI auto-scheduling, resource analysis, and predictive planning
2	Setup	Around 6 hours of manual machine parameter setting and validation	3 hours with AI-assisted parameter suggestions and validation
3	Manufacturing	Around 7 hours for manual operation, setup changes, and quality monitoring	5 hours using AI-based process optimization and real-time monitoring

Referencing Table 2, we can conclude that Integrating AI in manufacturing cuts planning time from 3 days down to just half a day, reduces setup time from 6 hours to 3 hours, and shortens manufacturing time from 7 hours to 5 hours. This significantly enhances overall efficiency and productivity.

Benefits of A.I in Manufacturing

- Improved productivity: AI will analyze data from real-time production processes and compare them with the historical data to find any minute deviations using sensors and machine learning techniques to optimize machine parameters, settings, and schedules. This again would result in efficient cycle times and maximize utilization of equipment. It reduces overall production time with improved accuracy and performance

- Automation: AI-powered machines or automation process can perform repetitive tasks with high accuracy, lower cycle time, and with less cost. This greatly reduces the human intervention needed for the given task, hence allowing the engineers to do more valuable and cost-effective tasks.
- Decision Making: AI algorithms analyze huge historical data set from the production data base and find out trends and parameters impacting product quality. Thus, enabling the engineers to make quick, effective, and correct decisions

Traditional Quality Process

Traditional quality processes primarily focus on detecting and correcting defects after they occur, rather than proactively preventing them. This reactive approach emphasizes inspection and control, aiming to identify non-conforming products or services before they reach the customer. While effective in identifying issues, traditional methods can be less efficient and may not address the root causes of quality problems(Westgard, 2015). These processes often rely on statistical process control, using tools like control charts to monitor key characteristics and identify deviations from established standards(Ali et al., 2016b).

A core component of traditional quality management is the analysis of non-conformities. This involves identifying and investigating instances where products or services fail to meet specifications (Ruffo et al., 2006). The goal is to understand the reasons for these deviations and implement corrective actions to prevent recurrence. Traditional approaches often include manual data collection and its analysis, which is time-consuming and prone to errors. Furthermore, the focus on post-production inspection can lead to delays in identifying and addressing quality issues, potentially resulting in increased costs and customer dissatisfaction(Bappy, 2024; Rashid, 2024).

Traditional quality management systems often incorporate philosophies such as Total Quality Management and Lean Six Sigma. TQM focuses a holistic approach to quality control, involving all members of an organization in continual improvement efforts. Lean Six Sigma focuses on reducing variation and eliminating waste in processes, using statistical tools and methodologies to identify and address the root causes of defects. While these philosophies can be effective in improving quality, their implementation within a traditional framework may still rely heavily on inspection and control rather than proactive prevention.

In contrast to modern quality management approaches, which emphasize prevention and continuous improvement, traditional methods often focus on detection and correction. This approach can be less effective in addressing the root causes of quality problems and may not be suitable for the complexities of modern production processes. The increasing adoption of Industry 4.0 technologies, such as the Internet of Things, Big Data, and Cloud Computing, is driving a shift towards more proactive and data-driven quality management approaches. These technologies enable real-time monitoring, analysis, and control of quality

Limitation of Traditional Mfg. Process

- Higher operational cost: Manual processes require more labor, and inefficient use of resources leads to increased expenses in terms of components wastage and cost
- Limited data utilization: Traditional methods struggle to analyze large volumes of Quality data, preventing the process from identifying trends, optimizing processes, and making data-driven decisions.
- Reduced competitiveness: Manufacturers without AI struggle to match the speed, efficiency, and cost-effectiveness of competitors who leverage smart technologies for innovation and growth.

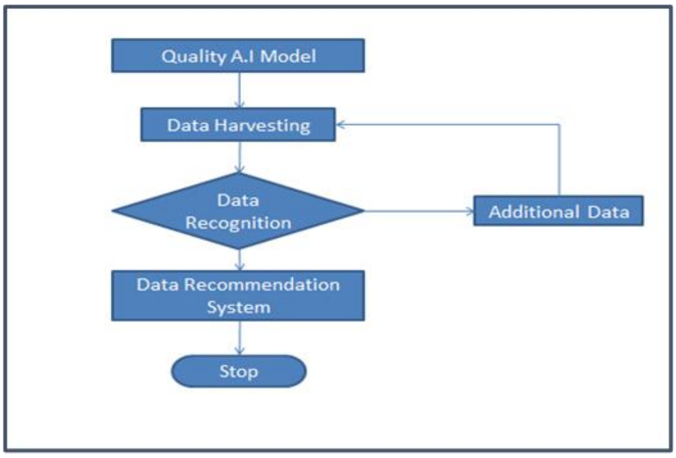
A.I Integration Into Product Quality (Smart Quality)

A.I In Manufacturing Quality Process is transforming the traditional quality control methods. Using Artificial Intelligence based Models and analysis of actual component vs historical data allows engineers to optimize real-time data analytics' accuracy as against the machine generated data model (Oyekan et al., 2019), for example, The smart quality system can analyze large chunks of operational historical real-time data with errors and accuracy and compare with the actual product data in order to identify real-time parameters of productions that may point toward probable failures or defects(Ahmed & Shaikh, 2022b; Bhatti & Dhamija, 2021). Along with the optimization in quality control parameters it also reduces inefficient downtimes hence improving continuous production accuracy and efficiency. The integration of AI with the machine learning data model not only streamlines quality control parameters but also enhances production accuracy that ultimately improves operational efficiency. Further, with AI capabilities to model complex variables, including real-time machine parameters turning to AI systems to enhance accuracy and personalize methods from industry to industry. AI model for machine quality epitomizes Integration of artificial intelligence into quality processes of the firms has altered the face of machine quality and control methods (Lee & Kwon, 2022). Using a sophisticated advanced data model, data analytics, the accuracy a shift towards a more responsive and smart data-driven approach to maintain the parameters of machine quality can be fine-tuned by the engineers, For example, AI Data models can analyze and filter through large historical data set of plastic bottle manufacturing batches and identify deviations that indicate a possible variance or inefficiency within the manufacturing process (Xi, 2021). These approaches can improvise the quality of product parameters; reduce downtimes in the process, and continuity of efficiencies. AI integrated with machine learning models would further help manufacturers optimize processes related to quality management and improve demand forecasting accuracy, aligning production more closely to market needs. As an example, AI might analyze production-line data to trace deviations in bottle weight or dimension and apply real time adjustments to maintain quality standards and prevent waste(Adeyemi, 2024)

Figure 3 shows a sample of the A.I based quality control architecture. For this to happen, the process should consist a few key steps

- Data harvesting: Collection of historical quality control batches data throughout the manufacturing process, inspection process data, tool performance data, downtown time and material properties data. The dataset compiled over time will help in spotting any deviations.
- Data collection includes live data: Gathering real time component data from the active batch and comparing with the accurate historical data using A.I based models/Algorithms to meet quality parameters and machine performance at the time of production, which allows immediate data analysis and enables the identification of problems much faster with timely corrective actions to maintain product quality.
- Recommendation System: Based on the real parameters of the components The A.I based recommendation system will provide the suggestions to alter in the current process based on the data from past manufactured batch, Manufacturing drawings and current parameters results.

Figure 3.Flow chart of A.I based quality architecture



Comparison (AI integrated vs Traditional Quality Approach)

Let's take a small example of a plastic bottle Quality Control process

Table 3.Results of time consumption between A.I & traditional approach for quality process

Sl. No.	Process	Traditional Method	AI-Integrated Approach
1	Material Inspection	Takes 3 minutes manually using visual inspection and basic tools	Takes 0.5 minute using AI-enabled image recognition and sensors
2	Quality Control	Takes 5 minutes for manual inspection and report documentation	Takes 0.5 minute using AI-based fault detection systems and real-time quality checks
3	Data Analysis	Takes 45 minutes using manual entry, Excel analysis, and charts	Takes 3 minutes with automated AI analytics and machine learning predictions

Referencing Table 3, Integrating AI into the traditional quality control process clarifies the gain in time efficiency. By applying sensors with automatic image recognition, material inspection and quality control times

Benefits of A.I in Quality

- Enhanced Accuracy and Precision: The use of A.I based quality control systems, can detect even the minute defects or inconsistencies that not be detected by the traditional methods. This includes minute surface cracks, imperfections, or color /size deviations
- Real-Time Component Monitoring: A.I systems intercept real time data and analyze with the data historical saved data and images in real time, providing innovative and quicker feedback about ongoing product.

RESULT AND DISCUSSION

The papers details a case study of plastic component manufacturing using the traditional vs A.I based method. Time taken for each stage is shown in the Table 4 for both the approaches. Referring table 4 the integration of AI significantly reduces the time required at each stage of the product lifecycle. For example, inspection time is reduced from 5 minutes to just 0.5 minutes, enabling faster decision-making and eliminating bottlenecks in high-throughput environments. Similarly, planning time is reduced from 3 days to 0.5 day, which enhances project agility and shortens the product development cycle. Each of these improvements not only boosts efficiency in individual phases but also contributes to a compounding effect across the entire workflow. These outcomes strongly support the central goal of this study — to demonstrate how AI-driven approaches can transform traditional mechanical engineering processes by improving speed, precision, and overall productivity.

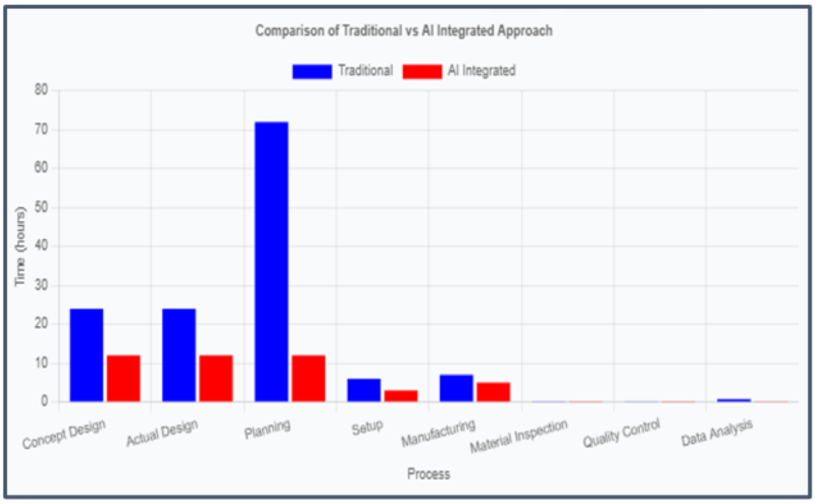
Table 4. Results of time consumption between A.I & traditional approach for overall process

Sl. No	Process	Traditional	AI Integrated
1	Concept Design	1 Day	0.5 day
2	Actual Design	1 Day	0.5 day
3	Planning	3 days	0.5 day
4	Setup	6 hrs	3 hrs
5	Manufacturing	7 hrs	5 hrs
6	Material Inspection	3 minutes	0.5 minutes
7	Quality Control	5 minutes	0.5 minutes
8	Data Analysis	45 minutes	3 minutes

Referring Table 4, and deep diving into the results data analysis we can observe that, AI integration within plastic bottle manufacturing increases in operational efficiencies in various stages of production. As can be seen in the present analysis, with the introduction of AI technologies, major reductions in time were achieved and, due to this fact, improvements in productivity and quality. Detailing the improvements in each areas below

- Design Phases: AI intervention at both the concept and. actual design phases reduced design time from 24 hours to 12 hours, which is a 50% reduction designer to try out different alternatives in a short time.
- Planning Efficiency: AI-driven tools transformed the planning process, which was required to be completed in 72 hours and was reduced to just 4 hours—a striking 94.44% reduction. It permits quicker resource allocation, scheduling, and smoother production workflows.
- Setup and Manufacturing: These were reduced from 6 hours to 3 hours, a reduction of 50% in setup time. In manufacture, these have been reduced from 7 hours to 5 hours.
- Quality Assurance: The introduction of AI-powered inspection systems raised the bar for quality assurance. Material inspection time was reduced from 3 minutes to just 0.5 minutes, which corresponds to 83.33%, while quality control went down from 5 minutes to 0.5 minutes, 90%. These automated systems ensure not only speed in inspections but also accuracy that helps in achieving higher quality standards
- Data Analysis Capability: AI reduced data analysis time from 45 minutes to just 3 minutes, which is a reduction of 93.33%. Much information can thus be processed in very little time to enable the derivation of actionable insights, thereby allowing manufacturers to arrive at decisions swiftly with scope for continuous improvement.

Figure 4 .Time Comparison of traditional vs A.I Integrated approach



The Cycle time reduction of the process is calculated using the formula

$$\left(\frac{97.8167 \text{ hours}}{133.8833 \text{ hours}}\right) \times 100 \approx 73.06\%$$

Thus, integration of AI in the whole manufacturing of a plastic bottle can overall reduce the time by about 97.82 hours, accounting for a 73.06% reduction in total processing time approx.

The results demonstrate an effective improvement in the efficiency of AI-based methods in reducing the cycle time required at the various stages of the product manufacturing cycle. The most impactful reduction is observed in the Planning Control, where AI visual inspection and data driven methods significantly reduces down the time required for traditional Plan methods. This suggests that AI models in mechanical areas can greatly can greatly enhance productivity and efficiency and reduce the cost in industrial processes. Figure 5 visually supports these findings, showing a consistent decrease in hours across all stages when AI is employed. This indicates a promising potential for AI to revolutionize traditional workflows, leading to faster and more cost-effective operations.

CONCLUSION

This study illustrates the benefits of leveraging and integrating Artificial Intelligence into the product development life cycle—design, manufacturing, and quality checking. Leveraging A.I can substantially improve efficiency, precision, and creativity. With the case study of plastic part production, AI-facilitated approaches cut overall development time by more than 70%, enhanced decision-making, and optimized essential processes. Inspection time was especially cut from 5 minutes to 0.5 minute, thereby boosting production throughput and responsiveness to defects. In parallel, planning and setup times were significantly reduced, making it possible to initiate projects and run them faster.

The findings can confirm the role of AI as a game-changer in mechanical engineering and its maturity for practical use. The implied practical implications are straightforward: organizations can gain quicker time-to-market, reduced expenditures, and better product quality through the integration of AI into current engineering processes.

Future research must be aimed at integrating AI at particular stages uncovered in this research. During the designing stage, CAD systems driven by AI can be extended to support real-time geometry optimization and performance simulation. During manufacturing, scheduling algorithms driven by AI can be extended to consider dynamic production parameters and shift scheduling. For quality control, more extensive integration of AI vision systems with real-time feedback loops can enable predictive correction prior to defects arising. Additionally, expanding datasets collected during manufacturing and testing can further train AI systems to become more accurate and self-learning over time.

By investing in these targeted areas, engineering teams can move beyond incremental gains to fully leverage AI's potential—driving faster innovation, smarter automation, and sustainable competitiveness in the Industry 4.0 era.

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