Review on Impact of Artificial Intelligent on Efficiency and Productivity in Industrial Automation

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[Submission: 17-05-2025, Accepted: 30-06-2025]

***Abstract*— As Industry 4.0 technologies evolve, the application of Artificial Intelligence (AI) in the manufacturing sector has become a major factor in improving operational efficiency, optimizing production processes, and reducing costs, enabling predictive analytics, data-driven maintenance, and automation of tasks that previously required human intervention. This study conducts a systematic literature review (SLR) on various AI methods applied in industrial automation, evaluates the effectiveness of their implementation, and identifies key challenges in their adoption. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and Population,**

Intervention, Comparison, Outcome, Context (PICOC) approaches are adopted. The sources used to search the literature included four electronic databases, comprising ScienceDirect, Taylor & Francis, Scopus, and Emerald Insight, resulting in 33 selected articles. The result shows that AI contributes significantly to improving production efficiency, but it still faces challenges in system integration, implementation costs, and workforce readiness. This study provides a comprehensive overview of the effectiveness of AI implementation in industrial automation and the challenges that need to be overcome to optimize competitiveness and production efficiency.

***Keyword*— Artificial Intelligence; Industrial Automation; Operational Efficiency; SLR PRISMA; System Integration Challenges.**

I. INTRODUCTION

The development of modern industry today shows a significant revolution characterised by the integration of advanced technology in manufacturing and operational processes. One of the most influential technologies in this transformation is Artificial Intelligence (AI). AI has become a significant catalyst in transforming industries' operations, from automated control systems and predictive maintenance to real-time supply chain optimisation and quality management.

In the Industrial Internet of Things (IIoT) context, AI replaces manual labour while contributing significantly to increased efficiency and productivity. This is possible through AI's ability to make quick and accurate decisions based on the large datasets generated by sensors and Internet of Things (IoT) devices. Integrating AI and automation is one of the main drivers in the transformation towards the Industry 4.0 era.

As the industry's reliance on AI technology increases, understanding the impact of AI implementation on operational effectiveness and productivity becomes increasingly important. Therefore, this research aims to comprehensively examine the role of AI in improving efficiency in the industrial sector through a Systematic Literature Review (SLR) approach. While research on the application of AI in industrial automation continues to grow, most of it remains limited to discussing AI techniques in isolation or specific case studies, without presenting a comprehensive synthesis of its overall contribution to improving efficiency and productivity across various industry sectors. Furthermore, it is rare to find a structured and comprehensive analysis that links the operational impact of AI with the implementation challenges and strategic direction of the future development of Industry 4.0. Therefore, this study presents a SLR that adopts the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) and Population, Intervention, Comparison, Outcome, Context (PICOC) frameworks. The aim is to evaluate the effectiveness of AI implementation in improving industrial efficiency and productivity, while identifying the real obstacles encountered in the implementation process.

Furthermore, this research also examines the contribution of AI in transforming increasingly complex and adaptive automation systems, as well as the extent to which AI can transform traditional work processes into more efficient and responsive ones, aligning with market dynamics. Additionally, this study identifies the potential of AI to open new opportunities, both through technological innovation and business model development. It evaluates its impact on the sustainability of industrial processes and long-term competitiveness in the face of increasingly competitive global competition.

The approach used in this study is the SLR approach as a structured and standardised method for collecting, analysing, and synthesising scientific findings from various relevant resent a thorough and objective perspective on the contribution of AI in industrial automation.

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The novelty of this study lies in its focused and systematic approach to analysing the impact of AI on improving industrial efficiency and productivity. Unlike previous general studies, this research presents a comprehensive synthesis of the current literature, accompanied by thematic mapping and analysis of relevant trends. The results of this study are expected to provide a strong scientific foundation for strategy development among academics, industry players, and policymakers.

II. Literatur Review

AI has improved productivity and operational efficiency in various industrial sectors [1]. One application is seen in optimising predictive maintenance and energy consumption, where AI-based automation can lower energy intensity per unit of output, as in China’s manufacturing industry. This efficiency is not only limited to the production process but also extends to logistics and supply chain management aspects. AI has improved productivity and operational efficiency in various industrial sectors [2]. One application is seen in optimising predictive maintenance and energy consumption, where AI-based automation can lower energy intensity per unit of output, as in China’s manufacturing industry. This efficiency is not only limited to the production process but also extends to logistics and supply chain management aspects. Supporting this, Permana et al. demonstrated how AI and automation could enhance energy efficiency and building operations through an intelligent building simulation system. Meanwhile, Anjani et al. implemented an IoT-based automatic retail system, showcasing real-time automation and decision-making in inventory and transaction management [3].

In this context, AI reinforces digital transformation by integrating machine learning technology and logistics automation, thereby supporting faster, more accurate, and more adaptive decision-making in response to market demand dynamics [4]. In addition to the logistics and energy sectors, AI also contributes to the design and manufacturing processes. When applied in real-time electrical load prediction and anomaly detection systems, AI can improve monitoring efficiency and optimize time and production material planning [5]. In the field of civil engineering, AI also accelerates the sustainable design process and reduces operational costs [6].

AI is widely used in machine control and equipment automation in production lines. For example, Phan examined the use of the Long Short-Term Memory (LSTM) model to control the movement of a 6-DOF welding robot arm and found that it can improve welding accuracy and reduce process errors [7]. A similar method was used in Rakholia et al.’s research to determine the time required for the food drying process. The XGBoost algorithm is also used for production planning and time efficiency in SCADA and ERP systems [8].

AI also monitors complex external situations in addition to internal systems. This system was created by Basmaji et al. to use drones to track the deformation of the anode kiln pit. This method uses YOLOv5 and DeepLabV3+ algorithms to speed inspection time while reducing human involvement [9]. However, this method faces problems when using AI in extreme industrial environments. Combining LSTM and Bayesian networks to adaptively drive pneumatic actuators to overcome system failures is another advancement in operational optimisation, as Skudlik and Wroble point out [10].

Controlling machine workload is also a concern in smart manufacturing. According to Iqbal et al., predictive optimisation-based task scheduling can improve machine utilisation efficiency, reduce idle time, and reduce production failure rates [11]. However, Sanchez et al.’s autonomic computing approach emphasises the system’s ability to reconfigure and make decisions autonomously throughout the data-driven production process [12].

AI also affects workplace relationships. Moniz et al. argue that the automotive industry’s adaptation of artificial intelligence increases efficiency, changes the way workers work, and alters their relationship with technology [13]. In addition, Liu et al.’s research shows that adopting artificial intelligence increases productivity and efficiency in various industries and strengthens countries in the global value chain [14]. In terms of machine maintenance, Cardaso and Ferreira suggest that AI-based maintenance predictors can improve the reliability of industrial systems and reduce failures by using historical data and algorithms such as Random Forest and Artificial Neural Network (ANN) [15].

The research shows that AI integration is highly beneficial in various industrial functions, such as supervision, maintenance, design, and decision-making. By making systems more productive, efficient, and adaptive, AI continues to change how modern industry works.

III. Method

A. *Systematic Literature Review (SLR)*

SLR is a scientific approach used to identify, evaluate, and synthesise all research relevant to a particular question or topic systematically and in a structured manner. The main objective of SLR is to provide a comprehensive understanding of the development of knowledge in a specific field and identify gaps or lacunae that have not been studied by previous research. The SLR implementation process is standardised through stages, from preparing research questions, determining inclusion and exclusion criteria, searching for literature, screening, analysing, and compiling review results. SLR can be done in quantitative analysis (meta-analysis) if the data allows, or in the form of qualitative narrative if statistical synthesis is not relevant with the PRISMA and PICOC approaches.

Table I the PICOC structure of the assessment questions related to the impact of AI in industrial automation.

TABLE I
PICOC METHOD

PICOC Element	**Description**	**Example (PICOC)**	**Example (Synonym)**
Population	Manufacturing and other industrial sectors that apply artificial intelligence (AI) in the	– Automotive Industry – Electronics Industry – Logistics Industry	– Digital Manufactu ring – Smart Factory – Industry 4.0

	automation process.		
Intervention	Application of AI in industrial automation, such as machine learning, deep learning, and predictive maintenance.	– Predictive Maintenance – Quality Control – Supply Chain Optimization	– Artificial intelligence – Predictive analytics – Industrial robotics
Comparison	Industrial automation systems without AI or conventional methods.	– Without AI: Conventional factories that rely on human labor – Without AI: Machine maintenance based on a fixed schedule – Without AI: Warehouse with manual record keeping	– Manual systems – Rule-Based Automation – Conventional systems
Outcome	Improved operational efficiency, productivity, and cost reduction.	– Operational Efficiency – Productivity – Cost reduction	– Process optimization – Operational effectiveness – Work improvement
Context	Industrial environments that use AI, such as smart factories and AI-driven logistics systems.	– Smart Factory – AI-driven logistics – Predictive Maintenance	– BPM (Business Prosess Management) – Industry 4.0 – Process modeling

The PICOC framework was used to formulate the focus of the study. Population refers to the manufacturing industry and other sectors that use AI in automation, such as the automotive and logistics industries. Intervention is the application of AI, such as machine learning and predictive maintenance, in industrial processes. Comparison compares AI-based systems with conventional methods like manual or human labour-based systems. Outcome focuses on outcomes such as increased efficiency, productivity, and reduced operational costs. Context is the modern industrial environment that supports the use of AI, such as smart factories or innovative logistics systems. Table II displays the research question used in this study:

TABLE II
RESEARCH QUESTIONS (RQ)

RQ	Description
RQ1	How does the application of artificial intelligence (AI) affect operational efficiency in industrial automation?
RQ2	How does AI contribute to improving productivity in industrial sectors that are implementing automation?
RQ3	What are the main challenges in implementing AI to improve efficiency and productivity in industrial automation?

From the table above, AI evaluation methods in industrial automation focus on production efficiency, productivity improvement, and implementation challenges. This study will assess how AI affects operational efficiency and identify challenges hindering its adoption in the industrial sector. RQ1 focuses on the impact of AI on production efficiency, RQ2 evaluates the comparison with traditional automation methods, and RQ3 identifies the main obstacles to AI adoption in the manufacturing industry.

The methodology that must be written down is the detailed steps of the research carried out, made in the form of a flow chart that the reader easily understands, and the letters are legible. Explain the detailed stages of the research, the data sources, data processing and results to be obtained. The methodology must be in line with the research discussion and the research results obtained.

B. Literature Selection

From the initial search phase, 1,180 articles related to the application of AI in industrial automation were found. However, not all of these articles can be used in this research. Therefore, a filtering process was carried out based on the title, abstract, and keywords, with the following results:

- 20 articles not processed.
- 1,080 articles were not processed further because they did not meet the criteria.
- 80 articles meet the requirements for the next selection stage.

At a further screening stage, the suitability of the abstracts was evaluated to ensure that the articles were truly relevant. From this process, 33 articles were found appropriate and used in this SLR study, while the remaining 47 articles met the selection criteria.

C. Literature Source

p-ISSN:1693 – 2951; e-ISSN: 2503-2372

Pre-applied search terms were used to locate papers and journals in relevant literature sources. The sources used to search the literature included four electronic databases, namely:

- ScienceDirect
- Taylor & Francis
- Scopus
- Emerald Insight

Searches were conducted on titles, abstracts, and keywords in these databases. For Scopus, the search only focused on the title because a full-text search can produce millions of irrelevant records. This review paper limits the literature search to 2020 to 2025 to make the information obtained more accurate and relevant.

D. Design Search Strategy

The design of this search strategy aimed to identify and collect relevant studies on the impact of AI on efficiency and productivity in industrial automation. The search process involved the following steps, which are also illustrated in Figure 1 as the visual representation of the systematic review process applied in this study.

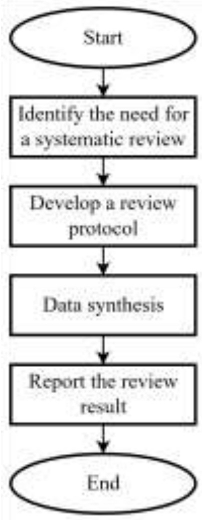

Figure 1 : SLR flowchart basic framework

The SLR method in this study was conducted systematically through several sequential stages, reflecting the principles of transparency and repeatability. The process began with the design of a search strategy using a combination of keywords relevant to the research focus. Then, the initial search results were filtered based on titles, abstracts, and keywords to eliminate articles that were irrelevant or inaccessible.

Articles that passed the initial stage were then analyzed in greater depth to assess the relevance of their abstract content to the research questions and the established inclusion and exclusion criteria. This stage was conducted in a stepwise manner to ensure that only high-quality and relevant articles were considered further. This screening and analysis process is illustrated visually in Figure 1.

E. Search Process

SLR requires a thorough search of all relevant sources. Therefore, the search process is defined and divided into two phases:

- Search Phase 1: A thorough search was conducted on the found literature sources, namely Scopus, ScienceDirect, Taylor & Francis, and Emerald Insight. The results of this search were compiled as a pool of potential literature. Next, inclusion and exclusion criteria were applied to filter out relevant studies.
- Search Stage 2: The reference lists of all relevant papers will be checked to detect studies that meet the appropriate criteria. This search will generate 50 relevant literature-pertinent citations to support analysing AI applications in industrial automation. Mendelay software (https://www.mendelay.com) stores and manages the selected literature results. An initial search was conducted across multiple databases using predefined keywords and filtering terms. The identified articles were screened through several stages based on their titles, abstracts, and keywords. This process excluded irrelevant and inaccessible articles. A total of 33 articles were ultimately selected after a deeper evaluation of their abstract content and alignment with the research objectives. The SLR process followed PRISMA stages, consisting of identification, screening, eligibility, and inclusion. Articles were categorized based on their relevance to RQ1–RQ3 through thematic analysis. Each RQ was addressed by classifying the articles into subtopics such as predictive maintenance, task scheduling, and system integration. These articles were used as the primary sources in this SLR. Figure 2 illustrates the PRISMA flow diagram summarizing the article selection process in this SLR.

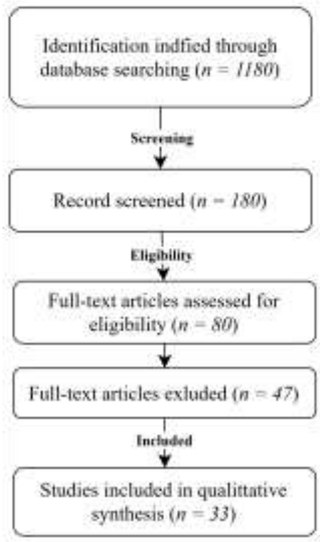

Figure 2 : PRISMA flow diagram of the article selection process, from 1,180 initial records to 33 studies included in the systematic review

From the selection process depicted in Figure 2, 33 articles were found to meet all criteria and were used as primary sources in this SLR. These articles were then analyzed to answer three main research questions (RQ1, RQ2, and RQ3).

IV. RESULT AND DISCUSSION

A. Analysis of Research Questions

The 33 selected articles were classified based on their relevance to the three main RQ. Articles discussing operational efficiency improvements through AI, such as predictive maintenance, downtime reduction, and production process optimization, were categorized into RQ1. Articles highlighting productivity improvements through automation, data-driven decision-making, and intelligent scheduling were categorized into RQ2. Meanwhile, articles discussing challenges to AI implementation, such as data privacy, high costs, and limited infrastructure and human resources, were classified into RQ3. Some articles covered more than one RQ, and these were taken into account in the analysis process. The results of the implementation and analysis of the three RQs are presented in detail in subsections B, C, and D of the discussion section.

B. Impact of AI Implementation on Operational Efficiency in Industrial Automation

The application of AI technology has shown a significant impact on improving operational efficiency in the industrial sector. Based on the analysis of several scientific articles, AI is used in various aspects of automation, ranging from system failure prediction and production scheduling to quality control and energy management. This integration contributes to reduced production downtime, efficient energy use, and increased accuracy and speed in operational processes.

1. Fault Prediction and Detection
   Numerous studies have shown that AI-based predictive maintenance can minimise disruptions in the production process. Systems that utilise machine learning and anomaly detection can accurately predict the condition of a tool or load, thereby preventing possible damage before it occurs [6], [15], [16]. This approach contributes significantly to reducing machine downtime and improving maintenance efficiency. In addition to the manufacturing sector, AI effectively identifies bottlenecks in the construction sector. The Nigeria case study shows that AI technology can identify structural bottlenecks early and support proactive asset retention. This implementation resulted in improved operational efficiency and a significant reduction in the risk of structural damage.
2. Production Process Optimization
   AI plays an important role in optimizing production processes. Research shows that the application of deep learning, deep neural networks, and predictive modelling can be used to schedule tasks, manage workloads, and optimize resource allocation efficiently [8], [11], [12]. This shows an increase in productivity as well as a reduction in wastage in the manufacturing process.
3. Improved Accuracy of Supervision and Quality Control
   Operational efficiency is also improved through the use of AI in automated monitoring systems. AI-based systems, such as LSTM models and classification algorithms, have proven effective in controlling robots or production lines in real-time [7], [17], [18]. The result is minimizing human error and improving the accuracy and consistency of the production process. In addition, AI-based predictive quality modeling is also leveraged to identify potential product defects from the customer's perspective.
4. Energy Efficiency and Resource Utilization
   A number of studies have specifically addressed energy efficiency in the application of AI in the industrial sector. One study showed that the use of AI can reduce the energy intensity of the manufacturing process [1]. In addition, AI also enables more efficient management of energy and material consumption through an integrated and sustainable system [5], [19].

C. Contribution of AI to Industrial Productivity Improvement

The application of AI technology has made significant contributions to the enhancement of industrial productivity. Based on the analysis of several scientific articles, AI is used to automate work processes such as welding and quality inspection, market demand prediction, production planning, and machine maintenance. It is also used for rapid decision-making through digital twins and for adapting production systems to changing conditions in real-time.

1. Repetitive Process Automation and Error Reduction
   AI has an important role in automating various repetitive production activities, such as welding processes, checking product quality, and monitoring production quality. The implementation of LSTM models in welding robot control systems has been shown to improve motion accuracy and overall work process efficiency [7]. On the other hand, the few-shot learning method used in defect detection systems enables high-speed inspection even when using only a limited amount of training data [20]. In addition, a Random Forest algorithm integrated into a quality control system for offset printing showed that AI can speed up the fault identification process while automatically maintaining product quality consistency [21].
2. Predictive Demand and Faster Decision Making
   AI has a very important function in production planning, especially through its ability to estimate market demand and optimize the delivery process. AI-powered systems can analyze past data to produce more accurate demand estimates, thereby reducing the

risk of excess inventory and defective products, and producing a more precise picture of demand trends [4], [22]. In addition, the application of AI in the concept of digital twin and design simulation is proven to be able to accelerate strategic decision-making, while increasing time efficiency and resource utilization in the industrial product development process [18], [23].

3. Rapid Adaptation to Production Variables
   One of the main advantages of applying AI in the industrial sector is its ability to improve the adaptability of production systems. AI gives the system the ability to automatically adjust operations to changing situations, such as variations in raw materials, product specifications, or production needs promptly [1], [24]. In addition, AI is also used to optimize assembly process scheduling, so that productivity is maintained despite changes in production line configuration or market demand [19].
4. More Efficient Management of Production and Maintenance Schedules
   AI is also used to manage production schedules and design maintenance systems that can anticipate operational disruptions to reduce potential downtime. AI in task scheduling and machine maintenance enables early detection of possible breakdowns, while supporting more efficient workload distribution [11], [15]. In addition, data-driven approaches and AI modeling have been shown to improve the accuracy of control systems and maintain the overall efficiency of the production process [10], [24].
5. Key Challenges Faced in the Implementation of AI in the Industrial Automation Environment
   The use of AI has proven to be able to support industrial operations that are complex and dynamically changing. One example is the application of AI-based autonomous drones used for inspection activities in a metal factory environment, which can speed up the inspection process without disrupting production [9]. In addition, the implementation of AI in the agro-industrial sector and food processing industry has also shown significant efficiency improvements, ranging from raw material selection processes, and automatic packaging, to controlling production parameters, with reported productivity increases of more than 20% [17], [26].

D. Key Challenges Faced in the Implementation of AI in the Industrial Automation Environment

Although AI has great potential to improve industrial efficiency and productivity, its implementation still has challenges. Based on the analysis of several scientific articles, these challenges include data quality and integration issues, limited resources, high implementation costs, labour resistance, and the complexity of integrating new technologies with existing systems.

1. Data Quality and Integration
   Most industries still experience difficulties in obtaining clean, complete, and integrated data. This is reflected in articles emphasizing the importance of real-time data integration in edge and IIoT systems [24], [27]. Data quality issues in practical AI model training are also raised in [20], [25]. Interestingly, issues in parameter calibration when using AI in offset printing processes were also highlighted from a manufacturing-specific perspective [21]. In addition, the importance of data transparency in human-focused AI is an additional issue discussed in [18]. Additional challenges related to data quality and completeness, data imbalance between products, and the risk of overfitting in developing drying time prediction models in the food industry are presented in [8].
2. Cost of Implementation
   Cost challenges often arise, especially in the early phases of AI implementation, including hardware, infrastructure, and training investments. This is explained in depth in an article that explores the difficulties in training large models such as GPT-3 and the need for organizational capability changes [28]. On the other hand, the realities faced by the small and medium-sized enterprise sector regarding limited funds hindering innovation were also raised in the article [24]. An interesting perspective is offered by an article that points out that even when AI has been implemented, productivity gains are not immediately apparent, giving rise to an investment dilemma [29].
3. Shortage of AI Human Resources and Competencies
   The issue of skill gaps is the primary focus in various articles. The importance of a phased and cross-functional training approach is described in [30]. Deficiencies in organizational readiness as well as barriers to workforce adjustment to new technologies are also outlined in articles [31], [32]. Furthermore, a strategic perspective on this challenge is presented in an article that emphasises that the issue is related to training and how companies can identify and realise value from AI [33].
4. Ethics and Worker Anxiety
   The social aspects of AI implementation often go unnoticed. The influence of AI on employee participation and job security is explicitly discussed in the article [34]. A symbiotic approach between humans and AI that differs from the full automation approach is introduced in [35]. Meanwhile, another article emphasizes the importance of building trust and paying attention to privacy aspects, thus providing an ethical and regulatory dimension to the application of AI in the industrial sector [18].
5. Complexity of System Integration
   The technical challenge of integrating AI with existing systems is a significant bottleneck in its application. The difficulties in real-time integration of digital twin and IIoT systems are described in [6], [24]. Further discussion on the importance of smart contracts and

organizational architecture that supports various technologies is presented in [19], [28]. Interestingly, a new approach is introduced through the concept of autonomic computing that shows the potential of adaptive and flexible manufacturing systems [12].

Future research should focus on developing standardized integration protocols for AI systems in SMEs, exploring ethical frameworks in AI-human collaboration, and establishing robust benchmarking datasets for predictive maintenance models in specific industries.

V. Conclusion

This research concludes that applying Artificial Intelligence in industrial automation significantly improves operational efficiency and productivity. AI integration can optimise various aspects, ranging from system failure prediction, production scheduling, and quality control, to energy and resource management, thus decreasing production downtime, energy use efficiency, and increasing accuracy and speed in operational processes. In addition, AI also accelerates decision-making by applying the digital twin concept, predicts market demand, and improves the adaptability of production systems to changing conditions. However, implementing AI in the industrial sector cannot be separated from various challenges, including suboptimal data quality and integration, high investment costs, limited human resources competent in AI, ethical issues from workers, and the complexity of integration with existing systems. The novelty of this research lies in presenting a comprehensive systematic review of the influence of AI on industrial efficiency and productivity while mapping strategic challenges and opportunities to support digital transformation in the industrial sector.

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