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Application of Artificial Intelligence in Electronics and Semiconductor Industries

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ABSTRACT

The global semiconductor industry is expected to reach $650 billion by 2024, spurred by the adoption of 5th Generation (5G), artificial intelligence (AI), and Internet of Things (IoT) technologies, making the electronics and semiconductor sector a key component of technological innovation worldwide. With 13% of the global market for semiconductor assembly, packaging, and testing, Malaysia is a key player. The electrical and electronics (E&E) sector contributes 5.8% of the nation's GDP and 40% of its exports. By improving fault detection accuracy to over 90% and lowering maintenance costs by up to 25%, the incorporation of AI into semiconductor production has revolutionized processes. The $5.3 billion National Semiconductor Strategy and Malaysia's Industry 4.0 goals align with AI-powered solutions that maximize productivity, anticipate equipment faults, and encourage sustainable practices. The review focuses on the integration and effectiveness of AI in the electronics and semiconductor industry including the utilization of AI in quality control and inspection, and inventory management. Emphasizing its impact on productivity, innovation, and global competitiveness particularly for fault detection, predictive maintenance, sustainable manufacturing practices, productivity enhancement, and economic contribution of semiconductors. The challenges of high energy consumption associated with AI infrastructure are also discussed. However, it is realized that the application of AI has greatly increased productivity, quality, and efficiency by reducing waste and managing to build robust and adaptable manufacturing ecosystems. Future advancements in AI, including digital twins and robotics, could create strong and flexible manufacturing systems, leading to a more innovative and resilient semiconductor industry.

Keywords: 5G, artificial intelligence (AI), Internet of Things (IoT), electronics and semiconductor industries

INTRODUCTION

The electronics and semiconductor sector are the foundation of contemporary technical innovation, driving developments in industries including consumer electronics, automotive, healthcare, and telecommunications. Due to the quick uptake of 5G, AI, and IoT technologies, the semiconductor market has expanded significantly on a global scale. The global semiconductor market is predicted to reach $650 billion in 2024 (Anonymous 2025), with the US, China, and South Korea leading the way in both production and consumption. Additionally, emerging markets are becoming more and more important in the global supply chain, especially in Southeast Asia.

In the global semiconductor ecosystem, Malaysia in particular has made a name for itself. With 13% of the global semiconductor assembly, packaging, and testing market, the nation is the sixth-largest supplier of semiconductors. The importance of the E&E sector to the national economy is demonstrated by the fact that it accounts for 40% of Malaysia's total exports and 5.8% of its gross domestic product (MIDA 2024). Furthermore, international semiconductor behemoths like Infineon Technologies and Intel have made large investments in Malaysian manufacturing facilities as a result of the country's advantageous supply chain location.

The industrial industry is adopting AI as a game-changing technology in line with worldwide trends. By increasing operational effectiveness, boosting product quality, and decreasing downtime through real-time analytics and predictive maintenance, AI is completely changing conventional manufacturing processes. Medium report (2024) claims that the use of AI in manufacturing can lower defect rates by as much as 40% and production costs by 15% to 20%. Through supply chain optimization, production schedule optimization, and equipment failure prediction, AI-powered technologies help manufacturers save a lot of money and increase efficiency. Table 1 shows the improvement realised by integrating AI in manufacturing.

TABLE 1. AI Integration Impact on Manufacturing (Medium, 2024)

Metric	Improvement Percentage
Productivity Increase	Up to 40%
Accuracy in Defect Detection	Up to 90%
Maintenance Cost Reduction	Up to 25%

The government of Malaysia has acknowledged AI's revolutionary potential in the semiconductor sector. By encouraging innovation, drawing in high-tech investments, and building a competent workforce, recent programs like the $5.3 billion National Semiconductor Strategy seek to establish Malaysia into a worldwide semiconductor powerhouse. Using cutting-edge technologies to stay competitive in the face of global issues including supply chain disruptions and rising demand for sustainable practices, AI integration in Malaysia's semiconductor industry is in line with larger Industry 4.0 goals.

The integration of AI into current manufacturing processes in the semiconductor and electronics sectors is examined in this paper, with an emphasis on how AI might increase output and reduce downtime. Additionally, it looks at Malaysia's place in the world semiconductor market and assesses how AI-powered solutions might boost the country's competitiveness. The paper highlights the significance of AI as a driver of innovation and growth in the semiconductor and electronics industries with insights backed by recent research and trends.

AI IN ELECTRONICS AND SEMICONDUCTOR MANUFACTURING

INTEGRATION OF AI IN ELECTRONICS AND SEMICONDUCTOR INDUSTRY

AI is a transformative technology that enhances various industries, including electronics and semiconductor manufacturing. By using advanced algorithms and machine learning, AI could optimize production processes, improve quality control, and increase operational efficiency. In the semiconductor sector, where precision and dynamic setting are crucial, AI plays a significant part in addressing challenges such as defect detection, predictive maintenance, and process optimization. As the demand for faster and more efficient chips grows, the integration of AI into manufacturing processes becomes essential for maintaining competitiveness and driving innovation.

The integration of AI into semiconductor manufacturing has transformed the industry in many ways. For instance, AI-powered process optimization analyses large amounts of production data to identify inefficiencies and make real-time adjustments, reducing cycle times and increasing the number of good chips produced. Moreover, predictive maintenance uses historical data and real-time monitoring to predict equipment failures, minimizing unplanned downtimes and extending machinery lifespan. In addition, AI contributes to energy efficiency by analysing usage patterns in manufacturing processes, identifying opportunities to save energy, lower operational costs, and support sustainable practices in semiconductor production (Brynjolfsson & Mitchell 2017).

Nowadays, AI has introduced numerous advancements in semiconductor manufacturing. For example, in defect detection, AI systems could automatically identify flaws during inspections, reducing reliance on manual inspections prone to human error. This can be done by using deep learning algorithms to continuously improve defect detection accuracy as they learn from new data (Mohandas et al. 2024). During the design phase on the other hand, AI accelerates simulations and identifies optimal design patterns allowing engineers to innovate more rapidly while ensuring designs meet strict performance standards (Zhou, Zhang & Yu 2023). Automated material handling is another example, where robots powered by AI simplify material handling duties in semiconductor manufacturing, boosting productivity while requiring less human involvement. These are a few examples of how AI is changing the industry, with numerous other innovations that contribute to increased productivity and sustainability.

In short, the integration of AI in semiconductor manufacturing not only enhances operational efficiency but also enriches innovation and quality assurance across the industry. As technology continues to evolve, the role of AI is expected to expand further, solidifying its importance in shaping the future of semiconductor production.

EFFECTIVENESS OF AI IN ELECTRONICS AND SEMICONDUCTOR MANUFACTURING

AI-powered predictive maintenance utilises advanced algorithms and machine learning to analyse data from equipment sensors, such as temperature, vibration, pressure, and noise levels, to detect subtle patterns and anomalies indicating potential failures. This proactive approach enables manufacturers to identify issues before they result in costly breakdowns, allowing maintenance to be scheduled during off-peak hours to minimize unplanned downtime. According to Dosluoglu and MacDonald (2022), AI-based predictive maintenance strategies can reduce machine downtime by up to 50%, leading to increased equipment availability, improved production consistency, and significant cost savings. The ability to predict maintenance needs also extends the lifespan of machinery, optimizes resource allocation, and contributes to higher production capacity.

The effectiveness of AI in the manufacturing industry is further demonstrated by its ability to enhance predictive accuracy through advanced machine learning (ML) techniques. As highlighted by Bonada et al. (2020), combining multiple ML models to make predictions significantly reduces global error, improving the precision and reliability of outcomes. This approach achieved impressive metrics, including a mean squared error (MSE) of 0.27, mean absolute error (MAE) of 0.40, and an explained variance score (EVS) of 0.98. Such accuracy allows ML models to simulate real sensor performance effectively during downtimes, enabling systems to continue operating without disruptions. This capability not only minimizes downtime impacts but also underscores AI's potential to maintain operational continuity and enhance productivity in industrial settings.

AI-DRIVEN QUALITY CONTROL AND INSPECTION

AI is transforming manufacturing processes, particularly in quality control and inspection, by boosting productivity and minimizing downtime. AI-powered computer vision systems are revolutionizing defect detection with unmatched accuracy and efficiency. For example, in Very Large-Scale Integration (VLSI) circuit manufacturing, convolutional neural networks (CNNs) can spot subtle layout errors that traditional methods often overlook, achieving precision and recall rates of over 97%. These systems process visual data in real time, enabling immediate defect identification and reducing delays in inspection (Ojha 2024). Additionally, dynamic feedback loops allow AI models to adapt to new fault patterns, ensuring continuous improvement and scalability for increasingly complex products.

Beyond defect detection, the benefits of AI in manufacturing extend to predictive maintenance and streamlined operations. By analysing fault trends, AI systems enable proactive interventions that minimize unexpected equipment downtime. In VLSI circuits, AI frameworks can detect intermittent faults with over 99% fault coverage, significantly improving product reliability and reducing waste (Ojha 2024). By automating labour-intensive tasks and ensuring rapid fault diagnosis, AI optimizes production lines and supports the development of intelligent, self-healing systems. As manufacturing technologies continue to evolve, AI's role in enhancing efficiency and maintaining reliability will become indispensable.

AI also plays a critical role in advancing quality control by improving consistency and reducing waste in manufacturing processes. The concept of Zero-Defect Manufacturing (ZDM), which aims to eliminate defects at their source, becomes achievable with AI's ability to analyse complex datasets and enhance decision-making. Industrial applications already leverage AI models like random forest classifiers and semi-supervised learning to identify and classify defects, even within imbalanced datasets. By applying supervised and semi-supervised machine learning methods, manufacturers can maintain consistent quality, reduce false positives and negatives, and significantly cut waste caused by defective products (Leberruyer et al. 2023).

Furthermore, AI enhances traditional quality methods by enabling early defect detection, which helps prevent downstream issues and optimizes production efficiency. Through data analysis, AI can identify patterns and predict potential defects, ensuring consistent quality. In ZDM, this proactive approach reduces reliance on manual inspections, which are often inconsistent and prone to errors (Leberruyer et al. 2023). Additionally, AI automates processes and balances defect detection with rework costs, ensuring sustainable manufacturing practices. While challenges like data quality and standardization remain, AI offers manufacturers a clear pathway to achieve higher productivity, reduce downtime, and drive continuous improvement through reliable, data-driven quality control methods.

AI is also revolutionizing manufacturing by automating quality assurance processes and enabling more efficient and accurate defect detection. For instance, AI-enabled all-textile sensors demonstrate how deep learning can enhance real-time quality control. These biodegradable sensors, integrated with convolutional neural networks (CNN), provide advanced data analysis capabilities for rapid and precise quality assessments. In manufacturing, such systems replace manual inspections with automated solutions that monitor production lines and detect irregularities early, thereby reducing waste and downtime. Moreover, AI algorithms can adapt to user patterns and operational environments, ensuring consistent performance and scalability across various applications (Zhao et al. 2024).

The adoption of AI for quality assurance not only boosts efficiency but also enhances sustainability in manufacturing processes. Systems like all-textile sensors offer eco-friendly alternatives by eliminating non-biodegradable components and allowing for natural decomposition after use (Zhao et al. 2024). This dual advantage of efficiency and environmental responsibility aligns with modern manufacturing goals, emphasizing productivity without compromising sustainability. By leveraging AI, manufacturers can implement automated solutions with high sensitivity and rapid response, seamlessly integrating them into existing workflows. These advancements not only enhance productivity but also minimize disruptions, paving the way for intelligent and sustainable manufacturing ecosystems.

OPTIMIZING INVENTORY MANAGEMENT WITH AI

Integrating AI into just-in-time (JIT) manufacturing enhances operational efficiency through real-time inventory tracking and demand forecasting. AI leverages machine learning and predictive analytics to monitor inventory levels, predict demand patterns, and optimize production schedules dynamically. This ensures raw materials and goods are available precisely when needed, reducing waste and improving responsiveness. By analysing historical and real-time data, AI provides actionable insights, enabling businesses to anticipate fluctuations in demand and streamline their supply chain processes effectively (Bonada et. al 2020).

Furthermore, AI minimizes material shortages and overstocking, leading to cost savings and improved reliability in JIT systems. It facilitates automated replenishment, better collaboration with suppliers, and timely adjustments to inventory and production schedules. This reduces storage costs, prevents production delays, and enhances overall supply chain resilience. AI-driven JIT systems enable organizations to transition from reactive operations to proactive, data-driven strategies, significantly transforming traditional manufacturing processes.

Integrating AI into JIT manufacturing could also significantly enhance supply chain operations by enabling real-time inventory tracking and demand forecasting. AI-powered systems analyse massive datasets to predict demand patterns accurately, ensuring the availability of raw materials and products exactly when needed. This capability not only reduces lead times but also minimizes waste, allowing businesses to maintain optimal inventory levels. By automating data analysis and providing actionable insights, AI supports agile decision-making, improving the responsiveness of JIT manufacturing systems.

In addition to optimizing inventory management, AI minimizes material shortages and overstocking, reducing storage costs and production delays. Intelligent systems facilitate seamless supplier collaboration and automated replenishment, enhancing supply chain transparency and efficiency. AI also supports predictive maintenance, ensuring operational continuity and reducing downtime risks. Overall, AI's integration into JIT manufacturing transforms traditional processes by increasing flexibility, reducing waste, and improving cost-effectiveness and customer satisfaction.

AI integration in the Malaysian retail industry enables precise JIT manufacturing and real-time inventory management through advanced analytics and machine learning algorithms. Retailers can enhance their forecasting capabilities to predict consumer demand, identify seasonal trends, and optimize inventory levels effectively (Mohamad Hafiz Mohamad Joned 2024). This predictive capability is crucial for ensuring product availability while minimizing waste and improving overall operational efficiency. The implementation of AI-driven systems allows retailers to analyse extensive datasets to synchronize inventory levels with actual consumer demand, reducing both material shortages and excess stock. Through real-time monitoring and data analysis, retailers can detect potential supply chain issues and implement proactive strategies to address them, ensuring smooth operations and maintaining optimal stock levels. This technological integration has become especially vital in Malaysia's retail sector, where consumer preferences can shift rapidly due to various socio-economic factors.

IMPLEMENTATION CHALLENGE ARTIFICIAL INTELLIGENT IN MANUFACTURING PROCESS

Implementing AI in the manufacturing sector offers transformative potential but comes with significant challenges that require careful navigation. From Li et al. (2024), their mention of the challenge in using artificial intelligence in the manufacturing process is that one of the foremost obstacles is the high energy consumption associated with AI infrastructure, such as data centres and model training. While AI can optimize production processes and reduce energy intensity, its operation often demands substantial energy, potentially offsetting its environmental benefits. To address this, manufacturers must integrate renewable energy sources and adopt energy-efficient algorithms and hardware. Leveraging AI for energy management within factories can further minimize consumption and ensure a more sustainable approach.

Another critical challenge is the disparity in AI adoption across regions and enterprises. Privately-owned firms often experience more significant efficiency gains compared to state-owned enterprises (SOEs), which may struggle with operational inefficiencies and bureaucratic constraints. Additionally, smaller firms and businesses in underdeveloped regions often lack the financial resources and technical expertise to implement AI effectively.

The rebound effect poses another challenge, where efficiency improvements from AI inadvertently lead to increased energy consumption due to cost reductions. Moreover, firms should be educated on the potential risks of the rebound effect to encourage alignment with long-term environmental objectives.

Infrastructure limitations further complicate the implementation of AI, particularly in areas outside smart city initiatives. These regions often lack the advanced energy management systems that enable AI-driven optimization. Expanding smart city frameworks and offering cloud-based AI solutions can help overcome these barriers, allowing firms to access cutting-edge technologies without heavy upfront investment. Other than that, accurately measuring the impact of AI remains a challenge. Many firms struggle to quantify AI's contributions to productivity and energy efficiency due to a lack of standardized evaluation metrics. Developing robust analytics frameworks and utilizing AI itself for monitoring and optimization can provide actionable insights.

According to Peretz-Andersson et al. (2024), we can conclude the implementation challenge is that limited access to skilled talent remains a critical issue. The shortage of professionals with expertise in AI technologies, data analysis, and machine learning makes it difficult for SMEs to build the human capital required for successful implementation. This gap often forces companies to rely on external consultants, which increases costs and dependency.

Next, data-related challenges are prevalent. SMEs frequently lack the necessary data infrastructure to integrate and manage the large datasets required for AI systems. Issues such as unstructured data formats and poor data governance impede the effective deployment of AI applications, particularly in production and process optimization. Lastly, the challenge that we could get from this article is technological readiness and scalability are significant concerns. Many SMEs are not fully digitalized, which limits their ability to seamlessly integrate AI into their operations. For those that adopt AI, scaling the technology to meet growing business needs can be challenging without a clear roadmap or sufficient resources

Gao et al. (2024) also highlights the complexity of integrating AI into dynamic and diverse manufacturing environments and requiring tailored strategies to address them effectively. One of the key challenges is data integration and management. Manufacturing systems often generate massive amounts of data from various sources, including sensors, machines, and human inputs. However, this data is often unstructured, inconsistent, or siloed across departments, making it difficult to create comprehensive AI models. Companies need to invest in robust data governance frameworks and interoperable systems to ensure seamless data flow and usability.

Other than that, resistance to change poses a considerable obstacle. Employees and management may hesitate to adopt AI technologies due to fears of job displacement, high initial costs, or uncertainty about the technology's benefits. Overcoming this resistance requires clear communication of AI's value, coupled with change management initiatives and retraining programs to reskill the workforce. The scalability and adaptability of AI solutions also present huge challenges. Manufacturing processes are highly variable and often tailored to specific products or markets. Generic AI models may not address these unique requirements, necessitating significant customization, which can increase costs and implementation time.

FUTURE WORK AND RECOMMENDATION

AI FUTURE WORKS IN THE INDUSTRY

The use of AI nowadays is a one step forward for the manufacturing industry to develop more rapidly. The use of growing rapidly in manufacturing to help humans during the production. With the amplification of AI in smart factories or machines, it can enhance productivity and reduce downtime. Reducing the inability to meet production targets, overtime costs and potential penalties for late deliveries, maintaining the seller-buyer relationship and reducing profit margins. Many future works can be implicated to produce a better automated production by enhancing the AI's capabilities to overcome problems. Future works are highly focused on areas of research, development, or implementation that are needed for further exploration or improvement based on current findings, trends, or challenges, moving to a smarter manufacturing way and highly adaptive systems.

One of the revolutions of improvements and innovations that can be implemented in the electronics and semiconductor manufacturing sector are the concept of digital twins. This digital model will enhance the production by facilitating the operational phases, enhancing efficiency and reducing costs. In semiconductor manufacturing, digital twins are used to optimize the operational parameters of cluster tools, which are essential for wafer fabrication. By simulating manufacturing processes, digital twins help in predicting productivity and determining optimal operational parameters, significantly reducing cycle times and improving productivity (Hwang & Noh 2024). With the presence of this technology, we can compare the real time data with the digital twin model to improve the decision making, optimize the production and predict the maintenance that might occur, and overcome all the challenges during the manufacturing process.

Due to the use of increasingly high-tech AI, the use of robotics might increase. With the use of robotic elements, one can implicate the integration of collaborative robots, or known as cobots, which work alongside humans in manufacturing environments. In semiconductor manufacturing, cobots are used for handling silicon wafers, a task that requires precision and cleanliness. Cobots' ability to operate in cleanroom environments and their small footprint make them ideal for such applications, where space is often limited (Bogue 2023). With the use of sensors, a cobot can control its movement with the surroundings, working near humans without posing significant risks. The versatility of this technology can be used in various manufacturing sectors.

Another application of robotics is using Autonomous Mobile Robots (AMRs). This robotic technology is moving freely, increasing the flexibility to work in any manufacturing sector. With the use of sensors, this robot can function as if it were a human which can detect the surroundings. AMRs provide increased flexibility in production networks, allowing manufacturers to respond swiftly to changing customer demands without incurring excessive costs (Fragapane et al. 2020). This flexibility is achieved by AMRs in circular loops among workstations, which helps avoid congestion and optimize flow and load-unload phases. This robot can enhance smooth flow production by transporting finished products from workstations to storage areas, or delivering them to packaging stations, which can minimize the downtime for the transportation problems.

Figure 1 shows the illustration of recommendations for future works in implementation of AI in semiconductor industries.

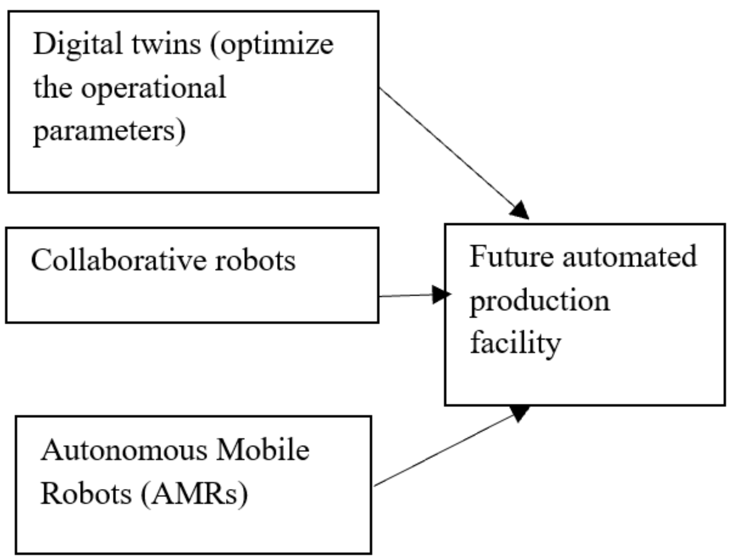

FIGURE 1. Recommendation for future work

AI INTEGRATION IMPROVEMENT AND RECOMMENDATION

To maximize the benefits of AI integration in manufacturing, companies must start by conducting a comprehensive assessment of their current processes. This involves identifying inefficiencies and areas where AI can bring measurable improvements. Understanding existing workflows and challenges helps in tailoring AI solutions to specific needs, ensuring effective implementation (Putha 2022). A robust data infrastructure is essential for successful AI integration. Manufacturers should establish systems to collect real-time, high-quality data from equipment and processes, as data accuracy directly impacts AI model performance. Additionally, proper data management practices are crucial to maintain integrity and facilitate analysis.

AI techniques should be carefully selected to address specific manufacturing needs. For example, supervised learning can be used for predictive maintenance, while unsupervised learning is better suited for detecting anomalies. Evaluating the strengths and weaknesses of different AI methods ensures that the most appropriate approach is chosen (Putha 2022).

Starting with pilot programs is an effective strategy to test AI solutions on a small scale before full implementation. This allows manufacturers to evaluate real-world performance and make iterative improvements. Such a gradual approach minimizes risks and ensures smooth scaling of AI applications (Rakholia, Suárez-Cetrulo, Singh, & Simón Carbajo, 2024). Integration with existing systems is another critical consideration. AI solutions must be compatible with current workflows to avoid disruptions. Developing APIs and interfaces that facilitate seamless communication between AI systems and manufacturing technologies ensures smoother transitions and operational continuity (Putha 2022).

Investing in workforce training is vital to ensure employees can effectively collaborate with AI technologies. Providing education on data-driven decision-making and enhancing technical skills empowers the workforce to adapt to AI-driven processes, fostering a culture of innovation and continuous improvement (Rakholia, Suárez-Cetrulo, Singh, & Simón Carbajo, 2024).

AI-driven predictive maintenance is one of the most impactful applications for minimizing unplanned downtime. By analysing historical and real-time data, AI can predict equipment failures, allowing for proactive maintenance and reducing repair costs (Chen 2017).

Finally, establishing feedback loops for continuous improvement ensures that AI systems remain effective over time. Regular performance evaluations and stakeholder feedback help identify areas for optimization, making AI solutions more adaptive to changing manufacturing needs (Rakholia, Suárez-Cetrulo, Singh, & Simón Carbajo, 2024).

Figure 2 summarised the recommendation for AI integration improvements.

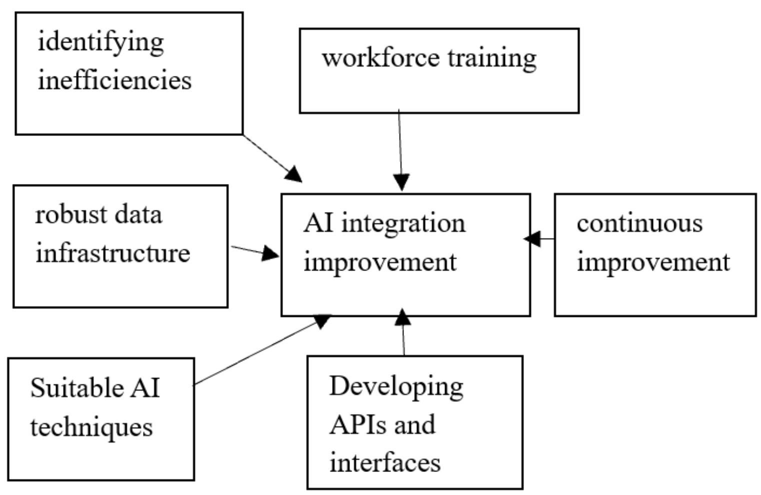

FIGURE 2. Recommendation for AI integration improvement

CONCLUSION

AI integration in semiconductor production solves important industry issues while greatly increasing productivity, quality, and efficiency. Predictive maintenance and sophisticated defect detection, two AI-powered technologies, have transformed manufacturing by cutting waste, operating expenses, and downtime. The goal of Malaysia's government programs and strategic investments is to establish the country as a leader in the world's semiconductor market. To fully realize AI's disruptive potential, however, issues including excessive energy consumption, a shortage of skilled labor, and data integration must be resolved. Future developments in AI-driven technologies, including digital twins and robotics, have the potential to build robust and adaptable manufacturing ecosystems, opening the door to a creative and resilient semiconductor sector.

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DECLARATION OF COMPETING INTEREST

None

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