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The Potential Impacts of Artificial Intelligence and Automation for the Malaysian Semiconductor Industry

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Abstract: - The semiconductor industry is a crucial driver of technological development, innovation, and advancement. In turn, modern technologies such as automation and artificial intelligence (AI) hold immense potential to enhance this sector's efficiency and productivity. By optimizing material utilization and minimizing defects, these technologies can lead to significant cost reductions, streamlined manufacturing processes, and improved product quality.

Despite the growing role of advanced technologies in this industry, there is a lack of systematic analysis addressing the opportunities and challenges they present. This paper aims to fill this gap by discussing the potential impacts of AI technologies on the Malaysian semiconductor industry. Through an analysis of existing research and real-world case studies, it seeks to provide insights into various AI techniques and their potential influence on the different stages of semiconductor manufacturing.

The study also highlights the current issues faced by Malaysian semiconductor firms and identifies areas for improvement. In addition, it offers relevant suggestions and recommendations to address these challenges. By reviewing various AI applications, their impacts, and existing challenges, this study aims to serve as a valuable guide for future research related to the Malaysian semiconductor industry.

Keywords: Malaysia, Semiconductor Industry, Automation, Artificial Intelligence, AI

1 Introduction

The Malaysian semiconductor industry is a pivotal contributor to technological advancements and innovation, significantly influencing our modern world's rapid progression. Semiconductors, characterized by their unique electrical properties that lie between conductors and insulators, are integral to a wide range of electronic components, including diodes, transistors, and integrated circuits (ICs). These components are essential in various applications, from automotive systems to wearable smart devices.

Malaysia's strategic role in the backend manufacturing of semiconductors underscores its importance in the global supply chain. The ongoing advancements in this sector are expected to amplify Malaysia's contribution to the international semiconductor market, bolstering productivity and fostering innovation (Lee et al., 2021). The sector's multiplier effect can significantly enhance national economic value by driving technological progress and economic growth (Batra et al., 2018).

Today, Artificial Intelligence (AI) stands at the forefront of technological innovation, with its transformative impact spanning multiple industries, including semiconductor manufacturing. Although AI is not a novel concept, recent advancements in machine learning have revolutionized its applications, impacting sectors ranging from healthcare to electronics. AI's capabilities in facilitating smart automation, enhancing human-machine collaboration, and enabling continuous process improvement are particularly relevant to the semiconductor industry. By optimizing production processes, AI holds the potential to significantly reduce costs and improve productivity and yield.

The Malaysian government recognizes the strategic importance of the semiconductor and electrical and electronics (E&E) sectors, as evidenced by their inclusion in national policy frameworks such as the National Investment and Manufacturing Plan (NIMP) 2030 and the 12th Malaysia Plan (MITI, 2023). NIMP 2030 outlines a mission-driven approach to fostering AI-driven value creation, emphasizing the development of generative and industrial AI solutions and system integrators (NIMP 30, 2023). By promoting an innovation-friendly environment, Malaysia aims to cultivate a competitive AI landscape.

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Additionally, the National Semiconductor Strategy (NSS) aims to position Malaysia as a global hub for the semiconductor industry within the next decade (MIDA, 2024). The NSS is designed to support and strengthen Malaysia's value chain while advancing its packaging, equipment, and automation technologies. This strategic focus is expected to solidify Malaysia's standing in the global semiconductor arena, driving economic growth and technological leadership.

2 The Contributions of this Paper

- This study undertakes a comprehensive analysis of the potential impacts of AI-driven algorithms on the optimization of Malaysia's semiconductor industry.
- It delves into various AI applications that could enhance different facets of the industry, offering strategic insights and recommendations to address existing challenges faced by Malaysian semiconductor firms.
- By discussing the current issues within the industry and presenting relevant suggestions, the paper serves as a critical guide for future research and policy development in leveraging AI for industry advancement.

3 The Exploratory Review

This study aims to conduct an extensive and comprehensive review of the literature concerning the potential impacts of AI-driven technologies on Malaysia's semiconductor industry. The review process begins by categorizing selected research papers based on their publication years and the journals in which they appeared. Following this initial categorization, a detailed refinement of applicable keywords is undertaken, leading to an in-depth analysis of the main study objectives.

To initiate the review, thematic and sub-thematic elements related to AI technologies and the semiconductor industry are identified and shortlisted. A targeted search of relevant keywords across various online databases yields a preliminary set of seventy-one papers. These papers then undergo a rigorous screening process based on their titles, abstracts, keywords, publication years, and journals of origin.

The inclusion criteria focus on papers published post-2019 to ensure the capture of the latest developments and insights, while the exclusion criteria eliminate any papers published prior to this period. This meticulous selection process results in a final set of twenty-five papers deemed most relevant for detailed review.

The subsequent analysis provides a detailed understanding of how AI technologies are being leveraged to optimize various aspects of semiconductor manufacturing within Malaysia. This encompasses enhancements in production efficiency, predictive maintenance, yield forecasting, and quality control. By delving into these intricate details, the paper aims to offer strategic insights and recommendations to bolster Malaysia's position in the global semiconductor market and to foster future research and policy developments in leveraging AI for industrial advancement.

4 The Impact of AI in the Semiconductor Industry

Globally, there is a significant increase in the adoption or at least trial runs of automation and AI technologies among semiconductor manufacturing firms. Besides opening up new market opportunities, AI technologies are capable of performing predictive processes involving manufacturing and maintenance operations, leading to improved yield and organizational performance.

It is evident that accurate and efficient manufacturing processes are crucial in this industry. The rapid advancement of modern technology, including the Internet of Things (IoT), Big Data Analytics, cloud computing, automation, and AI, has made universal manufacturing processes more streamlined. AI can enhance manufacturing processes by accurately evaluating data, optimizing parameters, and initiating real-time adjustments. In a study by Zhi et al. (2023), the Computable General Equilibrium model was used with semiconductor firms' input/output tables to gain insights into resource constraints and supply chain interrelationships. The study also analyzed the financial viability of government schemes and private investments in smart manufacturing initiatives within semiconductor firms. Their findings indicate that investing in AI applications could improve the firms' performance by more than 10%.

However, the study also found that the adoption of AI technology could reduce the demand for workers by nearly 25%. Nevertheless, this adoption could result in an uneven distribution of earnings and unemployment (Chu et al., 2020). According to Arinez et al. (2020), the Deep Q Network can be utilized to tackle challenging scheduling problems in semiconductor manufacturing. The researchers also noted that advanced reinforcement learning methods such as DQN are more scalable and efficient. These methods could be utilized by Malaysian semiconductor firms to ensure more practical and streamlined production scheduling processes. Automated visual inspection systems can recognize and address semiconductor manufacturing defects (Gund et al., 2020), leading to better yield, reduced expenses, and higher profits.

Encouraging transformations are being observed within the semiconductor manufacturing sector, brought about by AI technologies. Various domains within this industry have been revolutionized, such as circuit design and wafer testing, inline monitoring, fabrication processes, and packaging. The impact of AI technology on circuit design has been shown to be significant, with predictive models and optimization algorithms speeding up iterations, enhancing creativity, and reducing errors. AI technologies also ensure that the chips involved in fabrication processes are more efficient, precise, and durable (Senoner et al., 2022).

Given AI's immense potential, researchers have attempted to apply multifaceted AI solutions to improve various domains within the semiconductor manufacturing industry. Some of the key findings are presented below:

4.1 Process Quality

AI is ready to greatly influence process quality in semiconductor production, essential for guaranteeing the reliability, performance, and competitiveness of semiconductor goods. Process quality pertains to the reliability and effectiveness of manufacturing processes in adhering to stringent industry standards. The intricacy of semiconductor manufacturing implies that even small changes in parameters can lead to significant yield reductions, rendering effective process management a continual difficulty. Conventional quality control techniques, which depend on past data and human expertise, are becoming insufficient, particularly given the extensive and intricate datasets present in contemporary semiconductor manufacturing. AI, especially explainable AI (XAI), presents possible solutions to these issues, facilitating automated quality management and offering greater understanding of the reasons behind process variations. This article explores the ways AI can boost process efficiency, minimize defects, and improve overall yield in semiconductor manufacturing.

4.1.1 Issues in Conventional Semiconductor Process Quality Control

The process of semiconductor manufacturing is intricate, consisting of phases such as wafer fabrication, photolithography, etching, deposition, and testing. Even minor changes in process parameters—including temperature, pressure, or chemical concentrations—can result in defects, reduced yield, and higher costs. Conventional quality control methods, such as statistical process control (SPC) and decision-making based on expertise, face constraints:

- **Data Complexity**

The process of semiconductor manufacturing produces substantial amounts of high-dimensional, non-linear, and noisy data, which makes it challenging for human operators to identify significant patterns. Conventional tools usually depend on basic metrics, lacking a thorough grasp of variation (Sofianidis et al., 2021).

- **Delay in Identifying Issues**

Conventional quality control usually detects problems after the process, resulting in delays and increased scrap rates, complicating the resolution of issues before substantial losses happen (Muhammad Raza Naqvi et al., 2024).

- **Limitations of Human Expertise**

Skilled operators can face difficulties in analyzing intricate datasets and pinpointing root causes, particularly when handling extensive, high-dimensional data (Hrnjica & Softic, 2020).

- **Insufficient Predictive Abilities**

Conventional approaches tend to be mainly reactive, concentrating on addressing faults after they emerge instead of anticipating and preventing them beforehand (Jada, 2023).

4.1.2 The Contribution of AI in Improving Process Quality

AI, particularly via machine learning (ML) and explainable AI (XAI), offers robust solutions to these issues, revolutionizing process quality management in semiconductor manufacturing. Machine learning algorithms can evaluate extensive datasets from sensors and manufacturing systems instantaneously, revealing concealed patterns and anomalies frequently overlooked by human operators. Moreover, AI leverages historical data to create predictive models that anticipate possible process failures and outline corrective measures (Rajat & Das, n.d.).

- **Real-Time Oversight and Anomaly Identification**

AI can persistently track production data and identify irregularities instantly. For instance, in wafer manufacturing, AI can monitor factors such as temperature, pressure, and chemical levels, identifying any deviations from set limits. This enables operators to implement prompt corrective measures, minimizing defects and enhancing process stability (An Chi Huang et al., 2023).

- **Predictive Quality Control**

In contrast to conventional systems that respond to defects after their occurrence, AI has the capability to foresee defects or yield losses prior to their manifestation. Through the examination of past data, AI models can predict when certain conditions might result in negative outcomes, allowing for preemptive improvements and minimizing waste (Latha & Shyamala, 2023).

- **Interpretable AI for Root Cause Investigation**

Although machine learning algorithms can identify patterns and irregularities, they frequently lack clarity, which complicates understanding the rationale behind their predictions. Explainable AI (XAI) tackles this problem by offering understandable explanations for decision-making processes. In semiconductor production, XAI aids in determining the process parameters or equipment settings that lead to defects, enabling engineers to accurately address root causes (Rajat Suvra Das, 2024). Research conducted by Senoner et al. (2022) revealed that implementing XAI resulted in a 22% decrease in yield loss by offering important insights into the elements influencing process quality (Sofianidis et al., 2021).

4.1.3 Summary

The Prospects for Process Quality in the Semiconductor Sector of Malaysia

Integrating AI into semiconductor production signifies a significant progression in managing process quality. AI overcomes the constraints of conventional approaches by facilitating real-time observation, anticipatory quality management, root cause investigation, and process enhancement. These abilities not only boost production but also strengthen the competitiveness and sustainability of the Malaysian semiconductor sector.

With the industry encountering greater demands to achieve elevated standards of quality and efficiency, embracing AI technologies will emerge as a crucial differentiating factor. Malaysian manufacturers, crucial to the global semiconductor supply chain, will find AI-driven quality control systems vital for thriving in a competitive landscape and addressing the increasing needs of the electronics sector. Ultimately, incorporating explainable AI into process quality management can minimize defects, decrease production costs, and enhance yield, supporting Malaysia's status as a leader in the global semiconductor industry.

4.2 Predictive Maintenance

The increasing need for semiconductors, spurred by progress in artificial intelligence (AI), the Internet of Things (IoT), and 5G technologies, has exerted substantial pressure on semiconductor producers to enhance output and minimize downtime. One of the most revolutionary technologies to tackle these issues is the incorporation of AI into predictive maintenance. Predictive maintenance employs AI and sophisticated analytics to foresee equipment breakdowns prior to their occurrence, allowing for proactive measures. In the semiconductor sector, where precision of equipment and operational continuity are vital, AI-powered predictive maintenance can deliver significant efficiency improvements, cost reductions, and enhancements in product quality. This article examines the function of AI in predictive maintenance in Malaysia's semiconductor sector, highlighting its advantages, drawbacks, and prospects for the future.

4.2.1 The Present Condition of the Malaysian Semiconductor Sector

Malaysia plays a significant role in the global semiconductor industry, especially in wafer manufacturing, assembly, and testing. The semiconductor sector, which includes multinational corporations such as Intel, Infineon, and Texas Instruments, in addition to national firms like Halcyon Electronics, plays a vital role in Malaysia's economy, accounting for approximately 7% of GDP and over 30% of total export volumes. Although robust, the industry encounters obstacles like growing complexity in production, stringent timelines, and a need for accuracy. Semiconductor manufacturing facilities (fabs) are complex settings, necessitating distinctly advanced machinery.

Inactive periods in these facilities can be expensive, leading to production holdups, elevated maintenance expenses, and diminished product quality. Predictive maintenance has therefore emerged as a crucial priority for enhancing operational efficiency and reducing unforeseen equipment breakdowns (Ucar et al., 2024).

4.2.2 The Function of AI in Predictive Maintenance

Predictive maintenance depends on data gathered from equipment sensors, which machine learning (ML) algorithms analyze to forecast possible failures. The aim is to perform maintenance solely when required, preventing unnecessary actions and minimizing downtime. Essential AI technologies employed in predictive maintenance comprise:

- **Algorithms for Machine Learning (ML)**

ML examines past maintenance records and current sensor information to recognize trends and foresee breakdowns. These algorithms have the ability to identify problems that might not be apparent to human operators, enhancing the precision of forecasts (Mourabit et al., 2020).

- **Internet of Things (IoT) Sensors**

Semiconductor manufacturing facilities are outfitted with diverse sensors that track parameters like temperature, vibration, humidity, and pressure. These sensors deliver immediate data that can help detect possible problems in machinery (Serradilla et al., 2022).

- **Data Analysis and Visualization Tools**

Following data collection, AI-driven platforms assess and display the information in visual formats that assist maintenance teams in making informed choices (Keleko et al., 2022).

- **Natural Language Processing (NLP)**

NLP can analyze maintenance logs and other text-based information to derive useful insights, including frequent recurring issues or the success of prior maintenance efforts (*AI Driven Approach for Predictive Maintenance in Industry 4.0*, n.d.).

Predictive maintenance holds significant importance in semiconductor production because of the highly specialized characteristics of the machinery. Failures in essential equipment, like photolithography systems, can lead to extended production delays and impact the quality of the finished products (Rajat & Das, n.d.).

4.2.3 Implementing AI-Powered Predictive Maintenance: Case Studies and Illustrations

Case Study 1: Failures Due to Vibration in Semiconductor Production

Research conducted by King and Curran (2019) utilized machine learning algorithms to forecast vibration-related malfunctions in semiconductor production machinery. Vibration plays a vital role in guaranteeing precise machine movements, and even minor variations can lead to defects. The research employed ML to examine vibration data and precisely forecast when machinery was prone to fail from excessive vibration, enabling proactive maintenance steps like recalibration. This greatly decreased random malfunctions and enhanced equipment accessibility (Ponrudee Netisopakul & Nawarat Phumee, 2022).

Case Study 2: Predictive Upkeep at Intel Malaysia

At Intel's Penang site, AI and predictive maintenance are utilized to oversee essential assets, such as wafer inspection systems. By utilizing real-time data, AI algorithms identify initial indicators of failure, like unusual temperature changes, enabling proactive scheduling of maintenance. This strategy has resulted in lower maintenance expenses and fewer production interruptions, enhancing maintenance plans and avoiding unwarranted downtime (Ponrudee Netisopakul & Nawarat Phumee, 2022).

4.2.4 Advantages of AI in Predictive Maintenance

- **Decreased Downtime**

AI assists in lowering unanticipated downtime by forecasting equipment malfunctions ahead of time, enabling maintenance to be arranged during off-peak periods. This is especially crucial in semiconductor production, where a few hours of unplanned downtime can become expensive (Ucar et al., 2024).

- **Cost Reduction**

Predictive maintenance prevents expensive emergency fixes by tackling problems before they worsen. By concentrating maintenance exclusively on essential actions, manufacturers can enhance resource utilization and lower operational expenses.

- **Enhanced Equipment Longevity**

Timely detection of problems aids in avoiding major breakdowns, prolonging the life of costly semiconductor machinery. This is vital in an industry where specialized machinery can be expensive to replace.

- **Improved Product Quality**

Predictive maintenance guarantees that machinery consistently functions within ideal parameters, minimizing the chances of defects in the end product. In semiconductor fabrication, even minor equipment issues can lead to significant quality problems in chips.

4.2.5 Obstacles and Constraints of AI in Predictive Maintenance

- **Data Quality and Accessibility**

The effectiveness of AI-driven predictive maintenance relies on the accessibility and quality of data. Numerous semiconductor fabs already gather extensive data, yet incorporating this information into AI systems necessitates strong data management and processing abilities. Mistakes or deficiencies in data may result in imprecise forecasts.

- **Substantial Upfront Costs**

Adopting AI for predictive maintenance necessitates a considerable expenditure on technology and expertise. For smaller semiconductor firms, the expense of implementing AI solutions might be unmanageable. Nonetheless, as AI tools grow increasingly cost-effective, this obstacle is gradually lessening.

- **Skill Gap**

The application of AI in predictive maintenance necessitates a skilled workforce that has knowledge in both semiconductor production and AI technologies. The lack of these skilled professionals can hinder the implementation and efficiency of AI solutions.

4.2.6 The Future of AI in Predictive Maintenance

The outlook for AI in predictive maintenance within Malaysia’s semiconductor sector is optimistic. As AI and machine learning continue to progress, predictive maintenance systems will grow in accuracy and reliability, resulting in lower costs and enhanced operational efficiency. With the growing prevalence of Industry 4.0 technologies such as AI, IoT, and big data analytics, semiconductor manufacturers will progressively depend on real-time data to enhance maintenance choices. In the years ahead, AI-powered predictive maintenance systems are anticipated to be utilized throughout all phases of manufacturing, enhancing prediction precision and minimizing operational risks.

4.2.7 Summary

AI-driven predictive maintenance provides considerable benefits for the Malaysian semiconductor sector, such as minimized downtime, cost reductions, prolonged equipment longevity, and enhanced product quality. Utilizing sophisticated machine learning and sensor information, manufacturers can transition from reactive to proactive maintenance, ensuring efficient and competitive operations. Nonetheless, effectively implementing AI in predictive maintenance will necessitate tackling issues like data quality, investment capital, and shortages of skilled personnel. As these obstacles are addressed, AI will become essential in enhancing Malaysia’s semiconductor industry, fostering ongoing innovation and productivity gains within the global supply chain.

4.3 Detection of Faults and Classification of Faulty Equipment

AI and automation technologies provide considerable abilities for identifying defects and categorizing malfunctioning equipment in semiconductor production. Fault detection and classification (FDC) are essential in sectors such as semiconductor manufacturing, where minor errors can result in significant yield reductions. This article examines how AI enhances FDC procedures by monitoring equipment states, detecting issues, and assessing malfunction severity using sensor information.

4.3.1 Importance of Fault Detection and Classification (FDC) in Semiconductor Production

The production of semiconductors entails intricate procedures like photolithography, etching, and deposition, necessitating exact control of various parameters. Devices utilized in these procedures are fitted with sensors to monitor conditions such as temperature, pressure, humidity, and electrical signals, producing real-time information on equipment status and production settings, referred to as Status Variable Identifications (SVIDs). FDC is crucial for two primary reasons:

- **Avoiding Equipment Malfunctions**

Early detection of issues minimizes downtime, repair expenses, and material waste (Kohl et al., 2024).

- **Guaranteeing Product Quality**

Minor equipment differences can lead to defects, affecting yield and product quality. Accurate identification of defects enables rapid actions to uphold excellent product quality (Schlosser et al., 2022).

Due to the intricacies of contemporary semiconductor manufacturing, AI and automation are progressively employed to improve FDC, guaranteeing enhanced efficiency and precision in fault identification (Safont-Andreu et al., 2023).

4.3.2 The Function of AI in Identifying and Classifying Faults

Artificial intelligence, especially machine learning (ML), is highly effective at analyzing extensive datasets and recognizing patterns that are difficult for humans to detect. In semiconductor manufacturing at FDC, AI is utilized in various essential operations:

- **Data-Driven Fault Identification**

AI analyzes extensive amounts of real-time sensor information (SVIDs) to identify minor changes that may indicate potential faults. By recognizing these initial errors, AI allows for preemptive measures to avert significant equipment malfunctions (Maged et al., 2024). For instance, Fan et al. (2020) implemented ensemble techniques such as Naïve Bayes and K-Nearest Neighbor (KNN) to categorize wafers as defective or non-defective based on sensor information, aiding in the early detection of possible problems (Qiu et al., 2023).

- **Predictive Maintenance and Fault Prediction**

AI utilizes historical sensor data to create models that forecast potential equipment failures. This assists manufacturers in planning maintenance ahead of time, preventing expensive interruptions and guaranteeing ongoing production. Predictive maintenance powered by AI can reduce costs and enhance outputs by avoiding unexpected failures (Tian et al., 2023).

- **Enhancement of Sensor Selection and Feature Development**

Semiconductor machinery is equipped with numerous sensors, yet not all yield valuable information for identifying faults. AI techniques such as Random Forests assist in pinpointing the most essential sensors, enhancing both data analysis efficiency and fault detection precision. Fan et al. (2020) showed how Random Forests can pinpoint the most valuable sensor data for predicting faults.

- **Automated Fault Classification**

After a fault is identified, AI algorithms determine its type and severity, directing suitable responses. Models like Support Vector Machines (SVM), Decision Trees, and Deep Learning have the capability to classify faults from small issues that need recalibration to significant problems that necessitate equipment repair. AI is capable of identifying the underlying causes of issues, allowing for measures to be taken to avoid future occurrences.

4.3.3 Advantages of AI-Enabled Fault Identification and Categorization

The semiconductor sector in Malaysia is a crucial component of the worldwide supply chain, featuring major firms such as WD, Intel, Texas Instruments, and Infineon running extensive operations in the nation. Utilizing AI for FDC offers numerous advantages:

- **Enhanced Efficiency and Minimized Downtime**

AI automates the identification and categorization of faults, boosting the speed and precision of decision-making. This minimizes downtime, boosts throughput, and improves operational efficiency in manufacturing facilities.

- **Enhanced Production and Product Quality**

AI facilitates the early identification of defects, stopping flawed items from moving forward in the production process. This minimizes waste and rework, enhancing product yield and quality. By pinpointing the causes of faults, engineers are able to modify processes to enhance product quality.

- **Cost Reduction via Predictive Maintenance**

AI-driven predictive maintenance enables semiconductor manufacturers in Malaysia to prevent expensive emergency repairs by anticipating failures and facilitating repairs during scheduled downtimes. This lowers maintenance expenses and prolongs equipment lifespans.

- **Quicker Time to Market**

AI-enhanced FDC speeds up fault identification and resolution, assisting manufacturers in adhering to production timelines and expediting product development. This shortens the time it takes to launch new semiconductor devices, an essential aspect in the competitive semiconductor sector.

4.3.4 Issues and Factors to Consider

Although AI provides evident advantages for FDC, challenges need to be tackled for effective execution in Malaysia's semiconductor sector:

- **Data Quality and Accessibility**

AI models need substantial, high-quality datasets for efficient training. Inadequate or flawed sensor data can result in suboptimal model performance. It is essential to guarantee dependable data gathering and administration.

- **Integration with Current Systems**

Deploying AI-driven FDC might necessitate considerable integration work, concerning both hardware and software, to guarantee compatibility with current manufacturing systems.

- **Skill Gaps**

The implementation of AI in semiconductor manufacturing necessitates qualified engineers and technicians who can design, implement, and manage AI systems. Ongoing employee training is necessary to satisfy these requirements.

- **Scalability**

With increasing data volumes, AI systems need to be scalable to manage larger datasets and more intricate models without sacrificing performance. Maintaining the efficiency and accuracy of AI solutions as production increases poses a challenge.

4.3.5 Summary

AI and automation technologies provide significant advantages in identifying and categorizing faults within the semiconductor manufacturing sector. In Malaysia, the adoption of AI-powered FDC procedures can boost operational efficiency, minimize downtime, elevate product quality, and realize substantial cost reductions. Nonetheless, effective implementation will necessitate tackling issues concerning data quality, systems integration, workforce skills, and scalability. As AI technologies progress, their role in reshaping Malaysia’s semiconductor industry will grow, fostering automation, innovation, and global competitiveness within the sector.

5 Conclusion

This study aims to analyze the role of AI in the semiconductor industry, with a specific focus on its relevance to the Malaysian sector. Due to the complexities inherent in semiconductor manufacturing, Malaysian stakeholders must utilize high-quality predictive models. This can be achieved by incorporating additional parameters and process phases beyond what is discussed in this paper. To address the potential increase in missing values that may arise with the addition of new processes, implementing error-free prognostication models integrated with Precision Automated Metrology Systems is essential.

Additionally, Malaysian semiconductor companies should prioritize developing robust methods for anonymizing data and securing data-sharing protocols to protect intellectual property, thereby preventing unauthorized access. Enhancing the interpretability of AI models is crucial, as it allows engineers to gain a deeper understanding and trust in AI-driven decision-making processes. Flexibility in AI models can be achieved by designing algorithms capable of handling noisy or incomplete datasets. Adapting existing manufacturing setups to ensure accountability, fairness, and transparency in decision-making processes is equally important.

Overall, this paper provides valuable insights into the potential impacts of AI technologies on Malaysian semiconductor manufacturers and associated stakeholders, including process engineers, scholars, technology providers, and key industry players.

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