



PLANNING MALAYSIA:

Journal of the Malaysian Institute of Planners

VOLUME 23 ISSUE 6 (2025), Page 272 – 286

A CASE STUDY ON THE DIGITAL TRANSFORMATION OF AUTOMATED DECISION-MAKING IN SEMICONDUCTOR INDUSTRY 4.0

Sufinah Dahari¹, Noradilah Ahmad Fadzil², Nurul Fazilah Hassan³

^{1,2} Smart Manufacturing Unit, Department of Research and Development,

³Department of Information Technology,

DOMINANT OPTO TECHNOLOGIES SDN. BHD., MALAYSIA

Abstract

Malaysia introduced the National Policy on Industry 4.0 in 2018 to drive the digital transformation of its manufacturing industry. However, due to rapidly evolving technological trends in Industry 4.0, such as artificial intelligence, machine learning, and IoT, there remains limited clarity on how Malaysian manufacturing companies can initiate digital transformation on a small scale while remaining cost-effective and competitive. This study develops a method by comparing specific Industry 4.0 elements within a semiconductor manufacturing company to achieve automated decision-making through digital transformation. The case study indicates that the nine elements of Industry 4.0 are not necessarily all relevant to the semiconductor industry; however, the framework can still be effectively applied to automate decision-making. Digital transformation activities can be implemented in phased approaches, enabling the company to clarify potential value, assess financial constraints, and fine-tune strategies to maintain competitiveness and cost efficiency.

Keywords: Digital Transformation, Industry 4.0, Automated Decision-making

¹ Corresponding author. Email: sufinah.dahari@dominant-semi.com

INTRODUCTION

In the semiconductor manufacturing operations, there are many tasks involved in innovating new products and mass-manufacturing it. At each task, many decisions need to be made from gathering the right data, validating, and securing the data quality, to analysing it. With Industry 4.0, many of these processes are supported by automated data collection through digital transformation. Industry 4.0 refers to the digitalization of manufacturing processes via flexible automation suitable for mass production (Shahzad et al., 2023), enabling companies to enhance productivity and operational efficiency (Dolgui et al., 2024; Che Haron, R., & Muhd Zafir, N.B., 2025).

Shahzad et al. (2023) identify nine key elements of Industry 4.0: big data analytics, the Internet of Things (IoT), cloud computing, autonomous robots, additive manufacturing, simulation, augmented reality, interconnected IT systems, and cybersecurity. While definitions vary, there is broad agreement that integration through IT systems is its core characteristic. This raises the question of whether implementing all nine elements is necessary to achieve Industry 4.0. Currently, research on the progression and scaling of digital transformation in manufacturing operations is limited (Soomro et al., 2021), and compelling case studies are crucial for guiding Malaysian manufacturers in adopting these technologies (Yeap et al., 2024).

This study aims to: (i) review Industry 4.0 progress in a Malaysian semiconductor manufacturing company that has implemented an automated decision-making blueprint and scaled digital transformation to gain firm-specific insights, (ii) simplify the Industry 4.0 concept by comparing the case study against the nine elements, and (iii) assess the impact of digital transformation on automated decision-making. The scope of this research focuses on digital transformation for automated decision-making in semiconductor manufacturing.

LITERATURE REVIEW

Digital transformation is critical for enhancing competitiveness in manufacturing through technologies such as automation, IoT, and data analytics. Despite these benefits, adoption among Malaysian manufacturing firms remains low (Abdulaziz et al., 2023; Boos, 2024). Management often cites high costs, uncertain returns, and technological complexity as barriers (Abdulaziz et al., 2023; Ahmed et al., 2024; Hose et al., 2023; M. Shuhaimi et al., 2024), while limited financial resources, lacked skilled personnel, and ineffective change management further restrict readiness (Ahmed et al., 2024; Müller et al., 2018).

Studies by Fortoul-Diaz et al. (2023) and Wu et al. (2024) demonstrate the potential of Industry 4.0 technologies but focus mainly on technical solutions, offering little guidance on organizational strategies for scaling transformation. To address these challenges, Abbatemarco et al. (2022) and Goecks et al. (2024)

emphasize the need to analyse successful real-world cases that demonstrate measurable benefits of digital transformation. They suggest that management should focus on selecting use cases with clear business advantages and develop practices that make the outcomes more tangible to stakeholders. Complementing these perspectives, Yılmaz, K. Ö., (2023) proposes a practical framework for managing digital transformation, introducing “psychological asset-related elements” within a digital maturity model - including organization, culture, digital ecosystem, strategy, leadership, innovation, customer experience, digital skills, and vision. Therefore, this study aims to fill the existing gap by examining how Malaysian manufacturing firms can effectively implement and scale digital transformation strategies to strengthen decision-making and operational competitiveness.

RESEARCH METHODOLOGY

Research Framework

A research framework was developed (Figure 1) to address gaps in the literature on scaling digital transformation for automated decision-making and to gain firm-specific insights through direct engagement with manufacturing companies. This study presents a case study of a Malaysian semiconductor company, examining its Industry 4.0 roadmap and digital transformation activities across two phases. In Phase 1, a survey was conducted following the implementation of a pilot automated decision-making system. In Phase 2, after scaling the system to additional areas, a second survey was conducted. The digital transformation phases are compared with Industry 4.0 elements, the company’s centralized system before and after transformation, and the transition from manual to automated decision-making models. The case study is also benchmarked against other manufacturing studies to assess broader applicability. Finally, the impact of digital transformation on automated decision-making is analysed to draw conclusions.

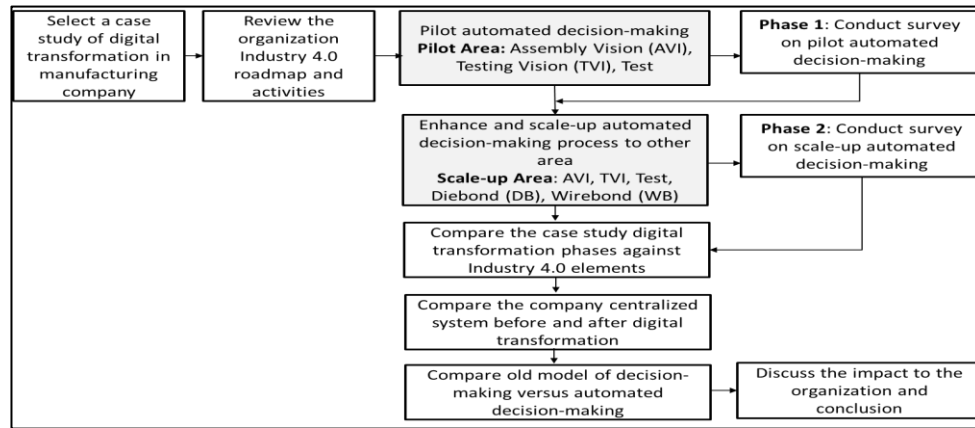


Figure 2: Research framework of case study

Case Study

Established in 2000, the case company is a local public-listed manufacturer of LED products for the automotive industry, producing 7,000–8,000 parts and operating six regional offices globally (The Edge Malaysia, 2025). The case company has committed approximately RM 1 billion for expansion, including Industry 4.0 digital transformation initiatives in Malaysia. In comparison, a global LED semiconductor firm has invested around RM 4.5 billion (equivalent to EUR 1 billion), highlighting a substantial disparity in investment scale between local and multinational firms in the sector within Malaysia (MIDA, 2025; MIDA, 2023). As of 2023, the company employs around 2800 employees with 260 in research and development (R&D), 85% of its employees aged 40 years and below with 51% of its employees are female. The company describes itself as a flexible and competitive manufacturer through extensive automation adoption (D&O Green, 2025). For the company to manufacture LED products, the raw materials will be processed in sequence through DB, followed by WB, then AVI before Test and TVI processes.

We reviewed all IT request form submissions related to digital transformation activities from 24 April 2019 to 28 November 2024. A total of 215 submissions were recorded. Examples of digital transformation activities include requests for additional data storage, data digitization, real-time reports, and interlocked recipe parameters through the IT system. IT request form submissions unrelated to digital transformation, such as new employee registration in existing IT systems, were not tracked. In 2022, the company implemented a pilot automated decision-making model in the AVI, TVI, and Test areas, focusing on process and product yield, which indirectly contributed to company profits.

Survey of the Digital Transformation Impact towards Automated Decision-making

All surveys were conducted online at different phases of the company's digital transformation. The online survey was implemented in two phases: Phase 1 (mid-stage of the centralized system) and Phase 2 (current stage of automated decision-making). The first survey gathered feedback from engineers supporting manufacturing operations on the company's piloted dashboards in 2022, which were used for yield analysis and data-driven decision-making. After the company refined its digital transformation strategies based on the results of the first survey, the second survey was conducted at a later phase to assess the impact of these improvements.

The target respondents of the surveys were engineers involved in manufacturing operations. To be eligible for selection, respondents' job scopes had to include supporting daily operational activities related to process quality and new product manufacturability. Engineers working in preventive maintenance, planning, and logistics were excluded from this study. Survey invitations were sent via email to the targeted respondents. Table 1 summarizes the demographics of the respondents. The variation in the number of invitations sent reflects the growing involvement of stakeholders as digital transformation activities expanded across different areas of manufacturing operations.

Table 1: Demographic of Targeted Respondents in the Phase 1 and Phase 2 Surveys

Demographic	Phase 1		Phase 2	
	Number of Invitation	Number of Respondents	Number of Invitation	Number of Respondents
Gender				
Male	5	3	23	15
Female	5	2	22	10
Job Title				
Process Engineer	5	4	30	20
R&D Engineer	5	1	10	3
Quality Assurance (QA) Engineer	0	0	5	2
Age				
<30 years old	3	1	10	8
30 – 40 years old	5	3	30	16
>40 years old	2	1	5	1
Total	10	5	45	25

Table 2 shows the survey periods for Phase 1 and Phase 2, along with the corresponding digital transformation phases.

Table 2: Phase 1 and Phase 2 Surveys Information

Information	Phase 1	Phase 2
Period	28th December 2022 till 30th December 2022	22nd October 2024 till 6th November 2024
Digital transformation phase	Mid stage of centralized system with 6 Dashboards for yield analysis visualization	Initial stage of automated decision-making with 18 Dashboards for visualization and 6 automated decision reports
Area	AVI, TVI and Test area	DB, WB, AVI, TVI and Test area

ANALYSIS AND DISCUSSION

Industry 4.0 – Digital Transformation Roadmap and Activities

The initial results present observations from IT request records across the company’s digital transformation phases, mapped against Industry 4.0 elements in relation to the automated decision-making model, followed by survey findings on digital transformation impact.

The semiconductor company follows its own Industry 4.0 roadmap (Figure 2). From 2019 to 2020, it focused on automated data collection from machines and sensors, identifying required data, ensuring quality, and standardizing formats for the internal IT system. In 2021, CSV data files were digitized into an SQL database and consolidated into a centralized web-based reporting system. Despite centralization, decision-making remained slow, as engineers still needed to export, clean, and analyse data in Excel. The company considered business intelligence tools, such as Power BI and Tableau, to accelerate data-driven decisions, but the high implementation cost relative to company size was a limiting factor.

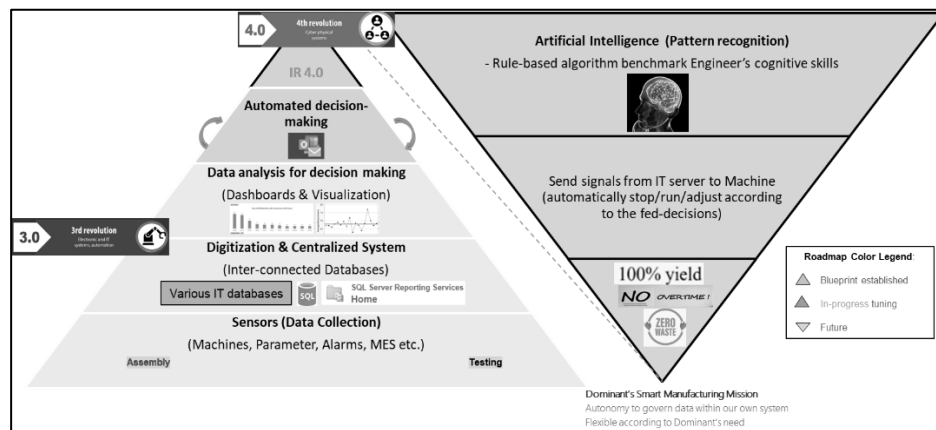


Figure 2: Industry 4.0 Roadmap of case company

Source: Courtesy from case company

In 2022, the company piloted Excel dashboards to support yield analysis and data-driven decision-making, enabling faster integration into engineers' daily workflows. The dashboards utilized Microsoft Office tools—Power Query, Pivot Tables, and Pivot Charts—to extract, summarize, and visualize data from the centralized repository. This setup allowed engineers to quickly assess current yield, top defect types, and machine performance, reducing reliance on manual data processing.

Targeted engineers in AVI, TVI, and Test areas were trained on the dashboards, and computer hardware was upgraded to handle larger datasets. Centralized data was automatically refreshed daily, allowing engineers to update analyses with a single click and customize scenarios (e.g., yield by product, machine, or combination). The established data pipeline streamlined investigations and accelerated decision-making. JMP statistical software was also deployed for ad-hoc and routine analyses, complementing the Excel dashboards and further enhancing the automation of data-driven decisions.

In parallel with establishing the digitization and visualization blueprint for decision-making, the company began integrating additional databases and IT systems—including equipment management, machine alarms, and recipe parameters—into its centralized system. To secure these data pipelines, cybersecurity infrastructure was also enhanced. As of 2024, the company is developing its own automated decision-making system using artificial intelligence (AI) technology. In the future, the company envisions that machines will auto-adapt based on AI-driven decisions to achieve the goals of smart manufacturing: 100% yield, no overtime, and zero waste.

Table 3 presents a comparison between the case study and Industry 4.0 elements. The company has implemented five Industry 4.0 elements: IoT, autonomous robots, an interconnected IT system, cybersecurity, and big data analytics. One autonomous robot was piloted in 2021, with an additional unit deployed in 2024. The company uses SQL-based computing rather than cloud computing. Regarding the primary characteristics of Industry 4.0, the company has established an integrated and interconnected IT system.

Table 3: Comparison between Case Study Digital Transformation Phases against Industry 4.0 Elements

Case Study Digital Transformation Phases (Industry 4.0 Roadmap)		Industry 4.0 Elements
Sensors (Data Collection and Data Quality)	At the early phase of digital transformation, the company emphasized on automated data collection for quality data from sensors such as process parameters, vision inspection, alarms through IT network. Through-out 2019 till 2024	IoT Autonomous robot

Case Study Digital Transformation Phases (Industry 4.0 Roadmap)		Industry 4.0 Elements
	to-date, 12 types of new “sensors” were introduced in the manufacturing processes. Examples of sensors are equipment manager, automated vision inspection, automated 2D and 3D profilometers, automated destructive bondtester, autonomous mobile robots.	
Digitization and Centralized System	In this phase, they have integrated various IT databases. As of 28 th Nov 2024, the company’s centralized system for manufacturing activities operating at more than 50 interconnected IT databases with different machine models and software vendors. Examples of IT databases are; machine alarms, process parameters, manufacturing execution system (MES), bill-of-material (BOM), statistical process (SPC) data and vision yield into centralized system.	Interconnected IT systems Cybersecurity
Data Analysis for Decision-making	The company used SQL, Microsoft Excel and JMP software for data analysis needed in manufacturing operation. The objective is mainly to explore trends, patterns, analyse variability and perform SPC analysis before rule-based algorithm for automation can be proposed.	Big data analytics Cybersecurity
Automated Decision-making through Artificial Intelligence	The rule-based algorithm used simple mathematical modelling and conditional logics that can be understood by the engineers compared to sophisticated machine-learning algorithms. There are several automated decision reports generated from rule-based algorithm. Example: • Daily report automatically validated the missing data issue for specific product or process and email to respective engineers to act. • Daily report automatically identified problematic machine that continuously triggering alarms or generating abnormal defectives item that can only be detected at next process within a day. • Real-time auto process control (APC) that tap input signal during wire bonding such as bond force, bond power and frame vibration and automatically trigger if signal exceed specified limit.	Big data analytics Cybersecurity IoT

Source: Author’s Observation

Table 4 presents a comparison of the company's centralized systems in 2019 and 2024, including interconnected databases and SQL tables. Between 2019 and 2024, the company's IT databases and SQL tables for manufacturing operations increased by 64% and 161%, respectively. These findings highlight the importance of IT infrastructure planning in scaling digital transformation activities. Comparing the digital transformation phases against the nine Industry 4.0 elements, as well as evaluating the centralized system before and after transformation and the old versus automated decision-making model, indicates that the company implemented new technologies in phases to better understand the risks and potential value of Industry 4.0 while navigating conceptual uncertainties.

Table 4: Company Centralized System (Interconnected Databases and SQL Tables)
Comparison in 2019 and 2024

System Name	Number of IT Databases		Number of SQL Table	
	2019	2024	2019	2024
Bill-of-materials (BOM)	2	2	141	143
Manufacturing Execution System (MES)	30	30	643	643
Machine Automated Recipe Parameters and Alarms Database	0	17	0	1,563
Machine Automated Vision Yield Database	0	1	0	15
Machine Automated Test Yield Database	0	1	0	267
Quality Database (SPC data and Production lot abnormality)	1	3	491	694
Total	33	54	1,275	3,323

Source: Author's Calculation

Comparing this case study with the research by Fortoul-Diaz et al. (2023), the common Industry 4.0 elements identified are IoT, an interconnected IT system, cybersecurity, and big data analytics with artificial intelligence. Unlike the literature case, the company in this study did not implement additive manufacturing. In our case study, the automated decision-making model uses digitalization and artificial intelligence as enablers for big data analytics, thereby simplifying the Industry 4.0 implementation.

Due to limited expertise in machine-learning technology, the company deploys a rule-based AI algorithm that mimics engineers' cognitive skills for pattern recognition. This approach also avoids the risks of AI "hallucination," such as falsely indicating critical process failures, which could disrupt manufacturing and quality activities. Figure 3 presents a comparison between the old decision-making model and the automated decision-making model.

For example, in identifying problematic WB machines, the previous method required engineers to repetitively gather and analyse data to answer several questions: (i) Which WB machine triggered non-stick on pad (NSOP) alarms continuously yesterday, and how many cases occurred? (ii) What are the affected lot details (e.g., product, lot quantity, number of alarms triggered)? (iii) Did the same WB machine also trigger abnormal WB-related vision defect losses at AVI post-WB process? (iv) If so, what were the vision defect losses detected at AVI, and how many cases occurred?

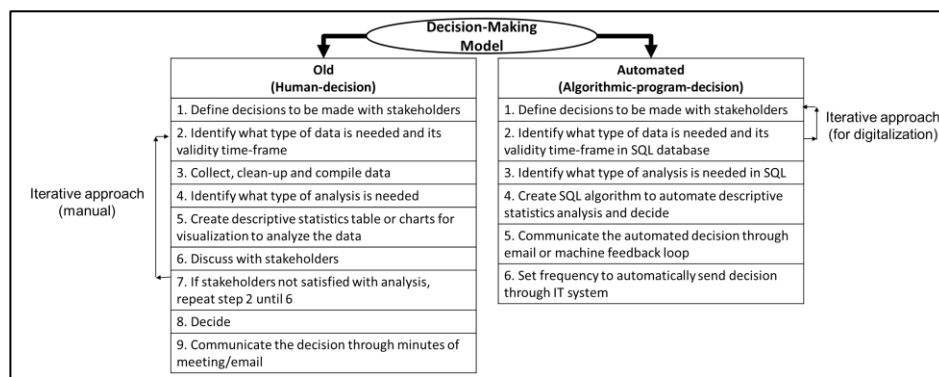


Figure 3: Comparison between the Old and Automated Decision-making Model

The above activities are time-consuming, often resulting in problematic WB machines not being identified in a timely manner and remaining undetected until they reach customers. In the current automated decision-making method, data is automatically extracted from the centralized system and systematically analysed by an SQL program to determine which WB machines are problematic. The SQL algorithm monitors continuous alarms at the WB process and/or abnormal defectives detected at AVI within a day. The thresholds for “continuous” alarms and “abnormal” defect losses are defined using a robust SPC chart (Dahari et al., 2025) and agreed upon by relevant stakeholders. Decisions are then automatically emailed to engineers to take appropriate corrective action. This eliminates the need for engineers to repeatedly gather and analyse data to identify problematic WB machines, making automated decision-making faster and more efficient than the previous model. These results suggest that other manufacturing companies can benefit from investing in automated technologies for data analysis and decision-making, which are crucial for advancing digital transformation.

Impact on the Organization

The company conducted surveys at different phases and adjusted digital transformation activities to fit the manufacturing environment. These surveys aimed to gather firm-specific insights into engineering decision-making using big data tools, such as dashboards and automated reports. Strategies from Abbatemarco et al. (2022), like selecting pilot areas with clear advantages (e.g., AVI, TVI, and Test), were used to promote adoption within the organization. Surveys during pilot phases collected stakeholder feedback, while follow-up surveys after scale-up validated the impact on the automated decision-making model. Both phases survey responses were then merged and analysed using thematic coding, where similar responses were grouped into main themes (categories) reflecting key aspects of dashboard use and digital transformation impact.

Table 5 summarizes the first survey and second survey response rate, which also revealed a weakness in the pilot online survey, as one respondent did not answer two questions. We have improved the online survey setup in Phase 2 to ensure all respondents complete all survey questions. Whilst, Table 6 summarizes the thematic findings, integrating both qualitative responses and quantitative measures.

Table 5: 1st Survey (2022) and 2nd Survey (2024) Response Rate

Main themes	1 st Survey	2 nd Survey
Dashboard Usage	100%	100%
Ease of Use & Training	100%	100%
Dashboard Features / Data Scope	100%	100%
Impact on Production / Tasks	80%	100%
Additional Features / Future Tools	100%	100%
Use of Time if Issues Addressed	80%	100%

Source: Author's Survey

Table 6: Thematic Coding Analysis Result

Theme	Key Findings
Dashboard Usage	Primarily used for yield monitoring; some track top defects by product/machine for process improvements. 84% use for yield improvement, 8% for data consolidation, 4% for inventory verification.
Ease of Use & Training	Generally easy to use, though some noted inflexibility and slow loading. 44% attended training and use it effectively; 52% did not attend or were unaware.
Dashboard Features / Data Scope	Users requested additional process details, comparisons, and interconnected process links. In second survey, time spent on dashboards is mostly ≤ 2 hours;

Theme	Key Findings
Impact on Production / Tasks	Dashboards represent production scenarios, though some noted inaccuracies. 96% said tasks would be inefficient if analysis were done manually.
Additional Features / Future Tools	Suggestions include separating engineering vs production yield, adding machine error logs, and extra formula columns. 60% prefer other BI tools or automated systems if dashboards are unavailable.
Use of Time if Issues Addressed	80% would like to spend more time for problem-solving flagged by the system rather than data mining. Addressing dashboard gaps allows users to focus on corrective and preventive actions to improve yield.

Source: Author's Survey

The case company has proactively pursued Industry 4.0 digital transformation as part of its broader expansion initiatives, which involve a total investment of approximately RM 1 billion. While this investment is significant for a local Malaysian firm, it remains substantially smaller than that of global LED semiconductor firms, reflecting resource constraints that may limit the adoption of advanced automation and analytics. The company currently relies on Excel-based dashboards and rule-based AI systems, which provide practical, cost-effective solutions for data aggregation, visualization, and routine decision-making. However, these tools are limited in scalability, and real-time analytics compared with machine learning-driven solutions that can enable automated process optimization.

To address these limitations, the company has developed a structured Industry 4.0 roadmap, providing a phased approach to digital transformation. Initiatives include integrating IT databases into a centralized system, upgrading hardware, improving internet connectivity, and providing training to strengthen engineers' data analytics capabilities. These efforts, combined with effective change management practices such as surveys at different stages of implementation and employee engagement initiatives, demonstrate a strategic approach to digital transformation (Ahmed et al., 2024). The relatively young workforce, with 85% under 40, and a balanced gender distribution further support technology adoption, highlighting the role of workforce demographics in shaping organizational readiness.

A critical consideration in the roadmap is the deliberate choice to utilize rule-based AI over machine learning at the current stage. Rule-based systems allow the company to standardize decision-making, maintain transparency, and reduce the risks associated with untested algorithms, which is particularly relevant given resource and expertise constraints. Nonetheless, this approach inherently limits adaptability and predictive capabilities, as the system cannot learn from new data patterns without explicit reprogramming. Machine learning,

while offering greater flexibility, predictive power, and optimization potential, requires larger datasets, computational capacity, and specialized skills—resources that may be challenging for a local firm to deploy immediately. The roadmap reflects a strategic trade-off: the company leverages rule-based AI for reliable, incremental gains while gradually building the infrastructure, skills, and culture necessary for machine learning adoption in the future.

Overall, the case illustrates a balance between incremental, resource-conscious digitalization and the transformative potential of Industry 4.0. The structured roadmap, investment in infrastructure, and targeted training initiatives reflect deliberate steps toward long-term digital maturity. By progressively incorporating scalable analytics and machine learning-enabled solutions, the company can enhance operational efficiency, competitiveness, and alignment with global industry standards. Incorporating organizational culture, leadership, and digital skills, as emphasized by Yılmaz (2023), will be critical for sustaining Industry 4.0 adoption and achieving sustainable competitive advantage in the LED sector.

CONCLUSION

This study illustrates how a local Malaysian semiconductor company successfully advanced its Industry 4.0 adoption through an automated decision-making approach, providing valuable insights for scaling digital transformation beyond pilot initiatives. Despite a smaller investment relative to global competitors, the company's phased and structured roadmap allowed it to evaluate benefits, manage costs, and iteratively refine strategies while progressively expanding digital capabilities. By integrating digitalization and AI, the automated decision-making model streamlines operations, reduces manual steps, and enables faster, more effective process and product improvements. The findings highlight a practical framework that can guide other semiconductor manufacturers in enhancing operational efficiency, fostering innovation, and strengthening industry competitiveness.

ACKNOWLEDGEMENT

This research did not receive any grant. The authors would like to thank Dominant Opto Technologies for consenting to be used as a case study for this research. The IT request records are confidential and proprietary information of the case company. The supplementary data such as the survey results and analysis method are available upon request to the authors.

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Received: 2nd September 2025. Accepted: 14th September 2025