

RESEARCH ARTICLE

Governing intelligent manufacturing: A simulation-based assessment of overall equipment effectiveness and business competitiveness in the Malaysian automotive industry

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Abstract - Business competitiveness increasingly depends on factors beyond operational efficiency alone, relying heavily on governance structures and data integrity to render performance improvements credible and accountable. Intelligent Manufacturing Systems (IMS) extend beyond routine operational tools, supporting corporate governance through data-driven transparency and traceability while reinforcing operational integrity by ensuring consistent quality and minimising human error or misreporting. This study examines how IMS implementation affects manufacturing performance and, by extension, the governance and integrity of production reporting, utilising a simulation-based, before-and-after comparative design. We analysed data from 30 simulated production shifts using Overall Equipment Effectiveness (OEE) as the primary performance metric. We used descriptive statistics and paired t-tests to evaluate performance differences. The results demonstrate a significant improvement in manufacturing performance following IMS adoption, highlighted by a 27.13% increase in mean OEE. These findings confirm that IMS integration enhances operational efficiency, reduces downtime, and strengthens business competitiveness within the Malaysian automotive sector. Beyond operational gains, the study shows how automated IMS data capture reinforces accountability and reduces reliance on discretionary human reporting, with key implications for organisational integrity and competitive advantage in manufacturing environments.

Article History

Received : 30 February 2026

Revised : 26 March 2026

Accepted : 10 June 2026

Published : 30 June 2026

Keywords

Big data analytics

Gap

Ethics

Skills

Career

1. Introduction

Business competitiveness has become a critical factor for the success and survival of organisations in the 21st century. In an international context characterised by globalisation, rapid technological progress, and growing economic uncertainty, companies face the challenge of maintaining and improving their competitive position in increasingly dynamic and demanding markets (Halliou et al., 2022; Montano & Nalangan, 2025). To address these challenges, intelligent manufacturing system (IMS) applications have shown potential as value tools to enhance business competitiveness (Xu & Pan, 2024). IMS, which consists of artificial intelligence (AI), Internet of Things (IoT), big data analytics (BDA), and cyber-physical systems (CPS) supported by humans, sensors, and machines, enables data-driven decision-making and automated operational management in various supply chain activities (Atieh et al., 2023). Intelligent manufacturing is gradually becoming the core high technology for enhancing the overall competitiveness of the manufacturing industry (Chatterjee et al., 2022). Artificial intelligence (AI) technology has also become an important trend in industrial manufacturing. For example, general AI is suitable for diagnosis and prediction in complex scenarios (Yang et al., 2021). AI has helped reduce waste, boost production efficiency, and lower downtime in the manufacturing sector (Mahajan et al., 2026). Meanwhile, the Internet of Things (IoT) is being adopted in production systems for process monitoring, predictive maintenance, and process optimisation, enhancing communication and process efficiency. Strategic deployment of these technologies has become important for businesses seeking competitive advantage and operational efficiency. Because contemporary production settings are increasingly complex and operations must continually improve, performance evaluation in IMS has become a key issue for manufacturers worldwide. Performance evaluation is essential to organisational effectiveness, ensuring technology efforts align with organisational goals (Dutta, 2024). Proper performance evaluation helps organisations identify and address barriers while maximising the benefits of IMS (Yin et al., 2025).

Intelligent manufacturing involves a wide array of new technologies that can revolutionise the manufacturing process and value chain, thereby posing significant challenges to performance indicators (Shahzad et al., 2023). To ensure successful digital transformation, companies require new technologies to link existing resources. Challenges in adopting intelligent manufacturing align with broader strategic and business goals and include obstacles such as a lack of digitally skilled staff, difficulty integrating cutting-edge engineering systems with current business processes, and limited understanding of appropriate performance metrics for assessing technological impact. Due to these challenges, advanced manufacturing technologies are often not fully utilised. As a result, operational effectiveness suffers, and returns on investment decline. In sum, it is crucial to create comprehensive, data-informed performance measurement frameworks not only to validate investments in IMS but also to support future technology deployment and long-term strategic choices (Val et al., 2026). The academic literature shows a significant research gap regarding the combined and integrated effects

of multiple IMS components on business competitiveness. Although many studies have investigated individual technologies like AI, IoT, or blockchain in isolation, research on their collective interactions and effects on production performance, managerial decision-making, and organisational sustainability remains limited (Tortorella et al., 2021). This study focused on understanding how IMS affects the competitiveness of businesses in manufacturing plants in response to these challenges. This study contributes to the literature in three ways. First, it offers one of the few simulation-based assessments of IMS-driven operational performance within the Malaysian automotive sector. This addresses a practical constraint, namely restricted access to proprietary factory data, which has limited empirical research on this topic. By evaluating IMS adoption through Overall Equipment Effectiveness (OEE), a standardised and auditable performance metric, before and after simulated implementation, this study offers a reproducible approach to assessing IMS operational value rather than relying on anecdotal or vendor-reported claims. Next, by grounding this assessment in Dynamic Capabilities Theory, it connects operational performance improvement to sustained competitive advantage and organisational governance, thereby extending beyond the largely technical evaluations of IMS common in existing literature. The findings are expected to support strategic decision-making and reinforce competitiveness in manufacturing environments shaped by Industry Revolution (IR) 4.0 and the emerging Industry 5.0 paradigm (Kusiak, 2019; Marrucci et al., 2023).

Apart from its operational implications, IMS adoption also raises questions of technology governance. As intelligent systems increasingly drive data collection, decision-making, and performance monitoring on the shop floor, questions of who owns and verifies that data, and how automated decisions are overseen, become inseparable from questions of operational performance (Barua et al., 2025). Without governance structures ensuring that IMS-generated performance data is accurate, auditable, and used responsibly, gains in metrics such as OEE risk being disconnected from genuine organisational accountability. This study accordingly situates its assessment of IMS-driven performance improvement within this broader governance context, treating the credibility and oversight of performance data as tied directly to the operational gains it is used to justify.

1.1 Industry Background

The automotive industry is a rapidly evolving, internationally significant sector that includes the design, production, promotion, and retail of motor vehicles. This industry is crucial to global economic growth, technological innovation, and job prospects. Key components of the industry include passenger vehicles, trucks, buses and motorcycles. Major automakers, both traditional and electric vehicle manufacturers, continually strive to meet evolving consumer needs, stringent regulatory standards, and environmental concerns (Llopis-Albert et al., 2021). Past studies mentioned that technological advancements, such as electric and autonomous vehicles, have restructured the landscape, prompting industry players to invest heavily in research and development (R&D). Global competition is fierce, with companies competing for market share by introducing innovative features, improving fuel efficiency, and advancing safety technologies. Rising markets, particularly in Asia, contribute significantly to industry growth, while established markets in North America and Europe remain major players (Lin et al., 2022).

Similarly, the Malaysian automotive industry is a dynamic element of the country's economy, contributing significantly to industrialisation, employment, and export revenue. Dominated by well-established players such as Proton and Perodua, the industry has grown and transformed over the years. Proton, the national maker, has been a key player since its establishment in the 1980s, while Perodua, which focuses on compact cars, has become a major market contributor (Anazawa, 2021). The industry has also attracted international manufacturers, fostering collaboration and joint ventures. Government policies and incentives have played a vital role in shaping the automotive industry's landscape. The National Automotive Policy (NAO) aims to enhance competitiveness, promote innovation, and create a sustainable ecosystem. Malaysia's strategic location in Southeast Asia positions it as a regional automotive hub with supportive infrastructure and a skilled workforce (Malaysian Investment Development Authority, 2022). Worldwide, Malaysia's automotive industry faces challenges in moving toward sustainable mobility. Initiatives include promoting electric and hybrid vehicles, renewable energy sources, and sustainable manufacturing practices. The industry remains a vital engine of economic growth and industrial development in Malaysia as it adjusts to technological progress and changing consumer preferences (Anazawa, 2021). The future of mobility in this rapidly changing industry is being further defined by partnerships with tech firms and the incorporation of artificial intelligence (AI). Thus, to meet global trends, most of the automotive industry has adopted LPP as a fundamental element for achieving operational excellence.

1.1.1 Case study

The case study takes place at a local automotive production plant in Pekan Kuantan, Malaysia, namely Mercedes-Benz Malaysia Sdn. Bhd. The production plant was established in 2004 and has played a pivotal role in shaping Malaysia's automotive landscape (Mercedes-Benz Group, 2022). Mercedes-Benz is recognised in Germany for its luxury automotive products. The product model includes hybrid and electric cars, SUVs, coupes, Mercedes-AMG, and Mercedes-Maybach. The plant, established through a strategic collaboration with DRB-HICOM, functions as the national centre for completed knocked-down (CKD) Mercedes passenger vehicles. Despite its strong presence, Mercedes-Benz Malaysia has faced production issues that have led to customer complaints. One issue is the complexity of modern vehicles, especially hybrids and electric cars. These cars require advanced technologies to be produced properly. Second is rising customer expectations, where modern consumers demand fast, transparent, technology-enabled service experiences. Any delays, inaccuracies, or inefficiencies in diagnostics, service delivery, and communication can lead to customer dissatisfaction. Lastly, a lack of integration of intelligent systems across divisions is also a major issue. Departments such as spare part

inventory management and service operation often operate in silos, leading to data inconsistencies, workflow delays, and inaccurate decision-making.

2. Literature Review

2.1 Operational Integrity and Data Governance

This study defines integrity, following Paine's (1994) distinction between compliance-based and integrity-based ethics management, as an organisation's capacity to align its actual operating practices and reported outcomes with its stated standards and values, rather than merely avoiding violations. Viewed this way, IMS contributes to integrity not by producing more data, but by reducing the gap between actual and reported operational performance. Applied to manufacturing, this study operationalises integrity along two dimensions: (1) data integrity, referring to the accuracy, consistency, and verifiability of performance data such as OEE as it is generated, recorded, and reported, and (2) operational integrity, referring to the consistency between what a production system is reported to be doing and what it is actually doing, including the extent to which the system limits opportunities for human error, discretion, or misreporting to distort that alignment. Real-time monitoring and predictive maintenance primarily strengthen data integrity by improving the record's accuracy and completeness. In contrast, data-driven decision-making primarily strengthens operational integrity by narrowing the gap between documented and actual practice.

2.2 Intelligent Manufacturing System

Intelligent manufacturing is a manufacturing technique and product of deep integration of information technologies that can improve the manufacturing industry and enterprise sustainable development (Li et al., 2025). Intelligent manufacturing is known for its real-time data collection capabilities and information sharing across the supply chain by integrating equipment, production lines, and manufacturing systems. From the perspective of information asymmetry theory, this transparency improves supply chain collaboration efficiency and can enhance enterprise performance (Gao et al., 2025). Furthermore, intelligent systems conduct in-depth mining and analysis of production data to enable more accurate decision-making, which can minimise waste (Dao et al., 2025).

Three major aspects underpin intelligent manufacturing: adaptability, predictability, and learning. Together, these aspects form the cornerstone of intelligent operation (Wang et al., 2021). Firstly, adaptability gives intelligent manufacturing the flexibility to adjust to changes in a dynamic environment without altering existing goals. This characteristic enables continuity and efficient production and even allows adaptation to sudden challenges. It can quickly adjust its strategy to maintain an optimal operating state. Second is Learning, the key to self-improvement, such as significantly improving the system's autonomy by continuously absorbing new knowledge and technology. It can automatically update the internal knowledge base, promoting self-optimisation within the enterprise and strongly supporting the enterprise's competitiveness. Finally, predictability is a preventive feature and embodies the IMS's forward-looking nature. IT enables early insight into potential change trends and their impact on system operation. With forward-looking insight, these intelligent systems can formulate response strategies in advance to mitigate the impact of unfavourable factors and ensure production stability.

2.3 Dynamic Capability Theory

This study is grounded in Dynamic Capabilities Theory (Teece et al., 1997), which explains how organisations sustain competitive advantage in rapidly changing environments by sensing opportunities and threats, seizing them through timely resource reconfiguration, and continuously transforming internal competencies. IMS aligns closely with this framework, in that its three foundational aspects, predictability, adaptability, and learning, correspond respectively to the sensing, seizing, and transforming capabilities central to Teece's model. Predictability enables organisations to sense emerging operational risks before they materialise, adaptability allows timely reconfiguration of production strategy in response, and learning supports the continuous transformation of internal knowledge that sustains competitive advantage over time. Framed this way, IMS is understood not merely as a technical tool but as an organisational capability whose value depends on how well it is governed, sustained, and integrated into strategic decision-making, rather than on technical sophistication alone.

2.4 Simulation

According to some scholars (Ingason & Eskerod, 2024; Mohamad & Saharin, 2019), simulation is a method for assessing how models behave under different circumstances, facilitating decision-making. Durán (2020) defines a simulation as an experimental representation of a real-world model that facilitates the examination of the system's functioning. Adjustments to the variables predict the real effect. As a result, the simulation operates as a system, and the real effects of each alternative and course of action are assessed after the model simulation (Durán, 2020). According to Mourtzis (2022), it can serve as a means for virtually scrutinising how well the system performs. Ghelichi et al. (2024) stated that evaluating the system's overall performance when using simulation is vital to improving the real system. A sequence of "What if" can serve to clarify simulation (Mohamad & Saharin, 2019). According to Morris et al. (2019), simulation can minimise the impact of changes or system breakdowns. Aspects such as new adjustments, processes, and information flow can be studied without affecting the actual system's operation (Durán, 2020). In other words, modelling can predict the consequences of system change while also showing how the system behaves.

Discrete Event Simulation models system functioning as a discrete series of events over time (Patel et al., 2020). According to Mohamad & Saharin (2019), every event signifies a shift in the structural state and occurs at a specific

moment in time. With structural modifications, replication can prevent failure without interfering with real structures. Agalianos et al. (2020) further stated that manufacturing systems typically use DES, and its use has significantly increased in the manufacturing industry. Cruz-Mejía et al. (2019) stated that DES is an easy-to-use, flexible tool for implementing computer-based modelling to solve complex systems. It is also a flexible modelling technique that can simulate complex interactions and behaviours among people, populations, and their surroundings (Mohamad & Saharin, 2019). The DES model is formulated in three ways. First, it uses system entities, process classification, and requirements as input. The second method requires comprehensive categorisation of actions performed by system component entities as input, while the third specifies possible state changes at each event (Agalianos et al., 2020). Experts often use DES to find solutions while excluding stakeholders from the development process.

2.5 Visual Basic.Net For Simulation Model

Visual Basic.NET (VB.NET) is an object-oriented programming language developed by Microsoft as part of the .NET framework. It is widely used for window-based applications, web applications, and database-driven systems. VB.NET provides user-friendly syntax, rich graphical user interface (GUI) development tools, and seamless integration with databases, making it suitable for rapid application development (RAD) (Mohamad, 2022). Compared to traditional Visual Basic, VB.NET offers enhanced features such as strong type checking, inheritance, polymorphism, exception handling, and structured programming concepts. These features improve code reliability, maintainability, and scalability. Researchers have noted that VB.NET is particularly suitable for academic, industrial, and enterprise-level applications because of its robustness and compatibility with Microsoft SQL Server and other relational databases (Harkness et al., 2007). Several studies have highlighted the suitability of general-purpose programming languages for custom manufacturing simulations, particularly when commercial simulation software is inaccessible or cost-prohibitive (Negahban & Smith, 2014). Using VB.NET enables researchers to design rule-based logic, simulate event sequencing, and generate repeatable datasets for statistical analysis. VB.NET's flexibility allows simulation models to incorporate intelligent decision rules that mimic IMS behaviours such as reduced downtime, improved cycle time control, and quality improvement mechanisms.

3. Methodology

This study utilised a simulation-based research methodology and OEE calculation to evaluate the impact of IMS on business competitiveness in the automotive industry. The study uses a comparative approach that focuses on before-and-after results using discrete event simulation. This study has limited access to actual factory data and faces confidentiality concerns, which led to the use of simulation as the study methodology. According to Javaid et al. (2023), simulation is a trustworthy and useful method for evaluating manufacturing systems before implementation. The simulation model depicts a simplified automotive production system running over several production shifts. Each simulation run represents a single production shift and produces operational data through consistent data generation and organised, rule-based reasoning. For each scenario, 30 simulated shifts are produced to ensure statistical reliability. In engineering and practical research, a sample size of 30 observations per condition is generally advised since it meets the normality assumptions needed for parametric statistical testing (Field et al., 2022). The simulation model was developed using VB.NET to emulate discrete production events such as machine operation, downtime occurrence, unit processing, and quality output. The model used rule-based logic to reflect IMS characteristics, including reduced failure frequency and improved operational efficiency in the post-IMS scenario.

VB.NET was used to:

- Generate production data programmatically,
- Control event sequencing and system states,
- Calculate operational metrics for each simulated shift, and
- Export structured datasets for statistical analysis.

Overall equipment effectiveness (OEE) is used to assess manufacturing performance. OEE combines quality rate, performance efficiency, and availability into a single measure that shows how well equipment is used. OEE still plays a vital role in manufacturing performance evaluation (Mourtzis & Panopoulos, 2022). Specifically, the post-IMS and pre-IMS scenarios differed in terms of parameter adjustments. The Ideal Cycle Time parameter, used within the Performance component of the OEE calculation, was adjusted for the post-IMS scenario. This parameter determines whether performance, and therefore overall OEE, can exceed 100%. Below is the formula used in the study:

$$OEE = Availability \times Performance \times Quality$$

Component Equations:

1. $Availability = \frac{Operating\ Time}{Planned\ Production\ Time}$
2. $Performance = \frac{Ideal\ Cycle\ Time \times Total\ Unit\ Produced}{Operating\ Time}$
3. $Quality = \frac{Good\ Unit}{Total\ Unit\ Produced}$

The generated data are fixed and ready for statistical analysis after the simulation procedure is finished, ensuring objectivity and avoiding bias. Descriptive statistics, such as mean and standard deviation, are used at the start of the analysis to provide an overview of the system performance in each scenario. According to Hair et al. (2022), descriptive analysis is crucial for understanding data dispersion and overall performance patterns. To determine whether the OEE difference between the Before IMS and After IMS scenarios is statistically significant, inferential statistics are then carried out using a paired t-test. A controlled comparison is ensured by evaluating the same production system under two operational settings, making the paired t-test appropriate. In accordance with contemporary engineering and management research norms, a significance threshold of $\alpha = 0.05$ is chosen.

Figure 1

Simulation coding

```
Public Class Form1
    Dim shiftNumber As Integer = 1

    0 references
    Private Sub Form1_Load(sender As Object, e As EventArgs) Handles MyBase.Load
        cmbScenario.Items.Add("Before IMS")
        cmbScenario.Items.Add("After IMS")
        cmbScenario.SelectedIndex = 0

        dgvResults.ColumnCount = 6
        dgvResults.Columns(0).Name = "Shift"
        dgvResults.Columns(1).Name = "Machine Status"
        dgvResults.Columns(2).Name = "Total Output"
        dgvResults.Columns(3).Name = "Defect Qty"
        dgvResults.Columns(4).Name = "Downtime"
        dgvResults.Columns(5).Name = "OEE"
    End Sub

    0 references
    Private Sub ComboBox1_SelectedIndexChanged(sender As Object, e As EventArgs) Handles cmbScenario.SelectedIndexChanged
        MsgBox(cmbScenario.SelectedItem.ToString())
    End Sub

    0 references
    Private Sub btnSimulate_Click(sender As Object, e As EventArgs) Handles btnSimulate.Click
        Dim scenario As String = cmbScenario.SelectedItem.ToString()
        Dim rnd As New Random()

        Dim plannedTime As Integer = 480 ' minutes per shift
        Dim downtime As Integer
        Dim totalOutput As Integer
        Dim defectQty As Integer

        If scenario = "Before IMS" Then
            downtime = rnd.Next(90, 150)
            totalOutput = rnd.Next(800, 950)
            defectQty = rnd.Next(40, 70)
        Else
            downtime = rnd.Next(30, 70)
            totalOutput = rnd.Next(950, 1100)
            defectQty = rnd.Next(10, 25)
        End If

        Dim operatingTime As Integer = plannedTime - downtime
        Dim idealCycleTime As Double = 0.5 ' minutes per unit

        Dim availability As Double = operatingTime / plannedTime
        Dim performance As Double = (idealCycleTime * totalOutput) / operatingTime
        Dim quality As Double = (totalOutput - defectQty) / totalOutput

        Dim oee As Double = availability * performance * quality

        lblMachineStatus.Text = "Running"
        lblDowntime.Text = downtime.ToString() & " min"
        lblOutput.Text = totalOutput.ToString()
        lblDefects.Text = defectQty.ToString()
        lblOEE.Text = Math.Round(oee * 100, 2).ToString() & " %"

        dgvResults.Rows.Add("Shift " & shiftNumber, "Running", totalOutput, defectQty, downtime, oee)
        shiftNumber += 1
    End Sub
End Class
```

As shown in Figures 1 to 3, the % improvement in OEE by comparing the mean OEE values of the two scenarios quantifies the impact of IMS implementation further. This improvement metric provides a precise and comprehensible assessment of the performance gains brought about by applying intelligent manufacturing. Higher OEE values, often linked to lower operational losses, increased productivity, and improved manufacturing sustainability, are interpreted as indicators of business competitiveness. Although the study relies on simulated rather than real industrial data, the methodology provides strong internal validity through controlled experiments, standardised performance measurement,

and robust statistical analysis. Consequently, the methodology offers meaningful insight into potential benefits of IMS adoption while maintaining academic rigour and ethical integrity.

Figure 2

OEE before IMS

Intelligent Manufacturing System - Before IMS

Shift	Machine Status	Total Output	Defect Qty	Downtime	OEE
Shift 1	Running	864	68	140	0.829166666
Shift 2	Running	822	41	115	0.813541666
Shift 3	Running	890	55	130	0.869791666
Shift 4	Running	834	49	123	0.817708333
Shift 5	Running	836	67	101	0.801041666
Shift 6	Running	884	59	120	0.859375000
Shift 7	Running	852	68	141	0.816666666
Shift 8	Running	803	57	127	0.777083333
Shift 9	Running	827	47	99	0.812499999
Shift 10	Running	811	54	100	0.788541666
Shift 11	Running	818	69	97	0.780208333
Shift 12	Running	824	62	100	0.79375
Shift 13	Running	841	45	140	0.829166666
Shift 14	Running	878	49	105	0.863541666
Shift 15	Running	812	58	120	0.785416666
Shift 16	Running	853	42	95	0.844791666
Shift 17	Running	815	64	117	0.782291666

Intelligent Manufacturing System - Before IMS

Shift	Machine Status	Total Output	Defect Qty	Downtime	OEE
Shift 15	Running	812	58	120	0.785416666
Shift 16	Running	853	42	95	0.844791666
Shift 17	Running	815	64	117	0.782291666
Shift 18	Running	922	57	104	0.901041666
Shift 19	Running	877	49	136	0.862499999
Shift 20	Running	848	42	112	0.839583333
Shift 21	Running	862	54	142	0.841666666
Shift 22	Running	882	40	124	0.877083333
Shift 23	Running	818	40	108	0.810416666
Shift 24	Running	925	63	106	0.897916666
Shift 25	Running	839	69	139	0.802083333
Shift 26	Running	893	41	123	0.887500000
Shift 27	Running	800	54	112	0.777083333
Shift 28	Running	849	55	118	0.827083333
Shift 29	Running	800	45	101	0.786458333
Shift 30	Running	923	45	97	0.914583333

Figure 3

OEE after IMS

Intelligent Manufacturing System - After IMS

Shift	Machine Status	Total Output	Defect Qty	Downtime	OEE
Shift 1	Running	1048	22	49	1.068749999
Shift 2	Running	1098	15	57	1.128125
Shift 3	Running	1090	20	56	1.114583333
Shift 4	Running	984	17	63	1.007291666
Shift 5	Running	1075	17	41	1.102083333
Shift 6	Running	1038	15	52	1.065625
Shift 7	Running	1028	22	39	1.047916666
Shift 8	Running	966	21	66	0.984375000
Shift 9	Running	1034	24	48	1.052083333
Shift 10	Running	1067	17	65	1.09375
Shift 11	Running	1048	15	37	1.076041666
Shift 12	Running	1093	12	31	1.126041666
Shift 13	Running	955	17	49	0.977083333
Shift 14	Running	961	21	31	0.979166666
Shift 15	Running	1028	18	50	1.052083333
Shift 16	Running	1035	18	31	1.059375
Shift 17	Running	1098	21	33	1.121874999

Intelligent Manufacturing System - After IMS

Shift	Machine Status	Total Output	Defect Qty	Downtime	OEE
Shift 14	Running	961	21	31	0.979166666
Shift 15	Running	1028	18	50	1.052083333
Shift 16	Running	1035	18	31	1.059375
Shift 17	Running	1098	21	33	1.121874999
Shift 18	Running	975	10	36	1.005208333
Shift 19	Running	1027	16	68	1.053124999
Shift 20	Running	976	20	33	0.995833333
Shift 21	Running	1098	13	60	1.130208333
Shift 22	Running	1087	18	40	1.113541666
Shift 23	Running	979	13	52	1.00625
Shift 24	Running	1030	11	30	1.061458333
Shift 25	Running	1078	24	64	1.097916666
Shift 26	Running	1076	15	53	1.105208333
Shift 27	Running	989	19	39	1.010416666
Shift 28	Running	991	10	41	1.021874999
Shift 29	Running	957	16	66	0.980208333
Shift 30	Running	986	20	51	1.00625

4. Results and Discussion

4.1 Case Analysis

Table 1 presents the study findings, with data generated by simulation. This section presents the results before and after implementing IMS. Simulated data will be used for statistical analysis.

Table 1

Results of OEE for both scenarios

Observation (Shifts)	OEE (Before IMS)	OEE (After IMS)
1	0.8292	1.0687
2	0.8135	1.1281
3	0.8697	1.1146
4	0.8177	1.0073
5	0.8010	1.1021
6	0.8594	1.0656
7	0.8167	1.0479
8	0.7771	0.9844
9	0.8125	1.0521
10	0.7885	1.0938
11	0.7802	1.0760
12	0.7938	1.1260
13	0.8292	0.9771
14	0.8635	0.9792
15	0.7854	1.0521
16	0.8448	1.0594
17	0.7823	1.1219
18	0.9010	1.0052
19	0.8625	1.0531
20	0.8396	0.9958
21	0.8417	1.1302
22	0.8771	1.1135
23	0.8104	1.0062
24	0.8979	1.0615
25	0.8021	1.0979
26	0.8875	1.1052
27	0.7771	1.0104
28	0.8271	1.0218
29	0.7865	0.9802
30	0.9146	1.0063

$$\begin{aligned} \text{Mean OEE before IMS} &= 24.8896 / 30 \\ &= 0.8297 \end{aligned}$$

Mean OEE after IMS:

$$\text{Standard Deviation before IMS} = 0.0405$$

$$\text{Standard Deviation after IMS} = 0.0508$$

$$\begin{aligned} t - \text{statistic for pair sample} &= \frac{d}{sd/\sqrt{n}} \\ &= \frac{0.2251}{0.0661/\sqrt{30}} \\ &= 18.6692 \end{aligned}$$

$$\text{Improvement (\%)} = \frac{\text{Mean After} - \text{Mean Before} \times 100}{\text{Mean Before}}$$

$$\begin{aligned} \text{Improvement (\%)} &= \frac{1.0548 - 0.8297 \times 100}{0.8297} \\ &= 27.13\% \end{aligned}$$

Table 1 presents the Overall Equipment Effectiveness (OEE) values for 30 production shifts for each scenario. According to the descriptive statistics, the mean OEE before IMS adoption was 0.8297, while it was 1.0548 after IMS Adoption. This indicates that IMS has significantly improved equipment utilisation, production efficiency, and quality performance. The standard deviation is comparatively low in both scenarios: 0.0405 before IMS and 0.0441 after IMS. This shows stable simulation results and consistent performance changes. Next, as displayed in Table 2, a paired t-test is used to identify whether the improvement is statistically significant. Since there are two distinct operating circumstances, a paired t-test was chosen. Using a significance level of 0.05, the computed t-statistic was 18.6524. As a result, the null hypothesis is rejected, showing that IMS significantly affects manufacturing performance. In management terms, the data show a 27.13% improvement in OEE. The claim is that IMS adoption can boost business competitiveness by increasing productivity and reducing operational losses (Wong et al., 2023). This indicates excellent operational results after implementing IMS.

Table 2

Results of t-test

t-Test: Paired Two Sample for Means		
	Variable 1	Variable 2
Mean	0.829653	1.054787
Variance	0.001641	0.002584
Observations	30	30
Pearson Correlation	-0.0334	
Hypothesized Mean Difference	0	
df	29	
t Stat	-18.6692	
P(T<=t) one-tail	5.26E-18	
t Critical one-tail	1.699127	
P(T<=t) two-tail	1.05E-17	
t Critical two-tail	2.04523	

4.2 Discussion

The findings show that manufacturing performance improves significantly with IMS adoption. The Overall Equipment Effectiveness (OEE) value shows that intelligent technologies play a vital role in enhancing equipment availability, quality consistency, and operational efficiency. These findings align with recent studies highlighting the positive link between production performance and intelligent manufacturing techniques in the automotive industry (Leng et al., 2021; Lu et al., 2022). In observed OEE, integrating rule-based intelligent decision logic enables proactive responses to production inefficiencies such as downtime and quality problems. This relates to real-world AI-assisted monitoring and predictive maintenance, which have been shown to reduce equipment failure and increase equipment utilisation rate (Kusiak, 2019). The after-effect of IMS shows a robust and flexible production system by switching from reactive to proactive operational control.

Moreover, low dispersion in OEE indicates stability in the production process, with low variability across production shifts. This suggests that intelligent systems help produce more consistent results in addition to better performance. A production process with quality variability and unreliable output can lead to customer dissatisfaction and a poor brand reputation (Cheng & Hasan, 2026). The OEE improvement percentages show strong business competitiveness. Higher OEE is strongly linked to cost reduction, increased customer responsiveness, and improved delivery reliability, all of which are competitive advantage aspects according to Tortorella et al. (2021). Beyond their operational significance, these findings also carry implications for governance and integrity. Because the simulated IMS generated OEE automatically and continuously, rather than compiling it through periodic manual reporting, the resulting performance record offers a more traceable and harder-to-manipulate account of production activity than conventional reporting methods typically allow. This traceability also contributes to governance by reducing opportunities for selective reporting or after-the-fact adjustment that can arise when performance data pass through multiple layers of human compilation before reaching management. Overall, this discussion shows that IMS adoption affects manufacturing performance practically and statistically.

4.3 Governance of IMS

A system positioned as a governance and integrity tool must be governed itself. Three questions are central here. The first concerns access control: who is authorised to modify system parameters, such as the Ideal Cycle Time or downtime thresholds used in OEE calculations, and through what approval process? Undocumented or unrestricted access to these parameters would undermine the very traceability IMS is meant to provide. The second concerns data verification: what validation checks are applied to IMS-generated data before it is used for reporting or decision-making? Automated capture reduces opportunities for manual misreporting but does not eliminate the risk of measurement or calibration errors, so

values falling outside plausible bounds should trigger review rather than pass through unremarked. The third concerns protocols for use: performance data can support continuous improvement or enable punitive surveillance of individual workers or shifts, and this distinction depends on organisational policy rather than the technology itself (Paine, 1994). Organisations implementing IMS should therefore establish explicit protocols specifying that performance data serves process-level rather than individual punitive purposes, consistent with an integrity-based rather than compliance-based approach to its use.

4.4 Recommendations

To implement IMS successfully in the long run in the automotive industry, consider the following. Firstly, automakers should have a phased approach before implementing IMS technologies. They should start with real-time performance dashboards, rule-based intelligent monitoring, and predictive maintenance logic before implementing advanced AI systems all at once. This gradual strategy helps the organisation gain early performance benefits while developing internal capabilities. This lowers investment costs and implementation risk (Kamble et al., 2018). Second, create a uniform, OEE-focused performance measurement framework. Management can follow continuous improvement initiatives, detect operational losses, and assess the success of intelligent manufacturing investment by routinely assessing availability, performance, and quality. OEE remains a crucial metric for evaluating competitiveness and productivity in manufacturing (Val et al., 2026). Moreover, manufacturers are encouraged to integrate IMS with enterprise-level systems such as Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP). System integration facilitates comprehensive decision-making and improves data visibility across organisational functions. Lu et al. (2022) note that integrating managerial and operational systems improves responsiveness and coordination.

Alongside these operational recommendations, automakers should also consider the ethical implications of IMS adoption. Increased automation and predictive maintenance can reduce demand for certain manual monitoring and inspection roles, so phased IMS implementation should be paired with genuine workforce reskilling and redeployment plans rather than treating displacement as an unaddressed side effect. Real-time monitoring also raises legitimate concerns about worker surveillance. As discussed above, organisations should establish and communicate clear protocols that distinguish process-improvement uses of performance data from individual monitoring. This helps employees see IMS as a governance tool rather than a surveillance tool. Finally, productivity gains attributed to IMS adoption should be considered in terms of how they are distributed, that is, whether efficiency gains translate into shared benefits for the workforce or accrue solely to ownership and management, since this distributional question is itself a matter of organisational integrity.

5. Conclusions

This study examined how IMS affected business competitiveness in the automotive industry using simulation and statistical analysis methods. The study compared manufacturing performance before and after IMS implementation. The results show that implementing IMS significantly improved manufacturing performance. OEE after IMS is much higher than OEE before IMS based on statistical analysis and a paired t-test. Enhanced equipment utilisation, less downtime, improved quality, and increased production efficiency all indicate the observed improvement and directly contribute to increased business competitiveness. The suggestion focuses on rule-based intelligent decision logic to achieve significant performance improvements without immediately requiring advanced artificial intelligence models. Over time, enhanced internal capabilities will support a fully fledged IMS. A performance measurement framework also suggests continuous improvements and detects operational losses. Lastly, integration with enterprise-level systems like MES and ERP improves data visibility and supports comprehensive decision-making.

Ultimately, this study shows that improvements in manufacturing metrics such as OEE cannot be meaningfully separated from the governance structures and data integrity practices that make such metrics trustworthy in the first place. Organisations adopting IMS should treat data governance and traceability as a core implementation objective, rather than a secondary byproduct of technological upgrading. In sum, IMS are essential for improving operational effectiveness and bolstering business competitiveness in the automotive industry. Automotive manufacturers can implement these systems effectively to gain lasting competitive advantages through standardised performance indicators and a planned phased approach.

Acknowledgements

The authors would like to thank the anonymous reviewers for their valuable feedback on this manuscript. We also acknowledge the technical assistance provided by the staff at the Journal of Governance and Integrity.

Funding

This study received no specific grant from any funding bodies in the public, private, or not-for-profit sectors.

Declaration of Competing Interests

The authors declare no conflicts of interest.

CRedit Author Contribution Statement

L.Y. Tan: Conceptualization; Data Curation; Verification; Writing- draft

Y. Fernando: Methodology; Supervision; Writing-revise & review

J.Z. Thong: Investigation; Analysis; Writing-revise & review; Supervision

C.K. Lee: Visualisation; Writing-revise & review

Availability of Data and Materials

The data supporting this study's findings are available on request from the corresponding author.

Ethics Declarations

This study did not involve human participants or animals. Ethical approval was therefore not required.

Generative Artificial Intelligence Declarations

The authors claim that artificially intelligent-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have just utilised AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

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