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Barriers to AI Adoption in Logistics Management within Manufacturing Industry in Melaka, Malaysia

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Abstract

This study examines the barriers to Artificial Intelligence (AI) adoption in logistics management within the manufacturing industry in Melaks, Malaysia. Although AI has been widely recognized for its potential to enhance operational efficiency, improve decision-making, and optimize supply chain performance, its adoption in logistics operations remains relatively low, particularly among manufacturing firms. This research aims to identify and analyze the key barriers hindering AI adoption, focusing on organizational resistance to change, cybersecurity and data privacy concerns, and high implementation costs. A quantitative research approach was employed, utilizing survey questionnaires distributed to manufacturing companies in Malacca. The collected data were analyzed using Statistical Package for the Social Sciences (SPSS) to examine the relationships between identified barriers and the level of AI adoption. The findings indicate that high initial investment costs, resistance to organizational change among employees, and concerns regarding data security and privacy are the most significant obstacles to AI implementation. Additionally, a lack of technical expertise and limited awareness of AI benefits further impede adoption. The study concludes that addressing these challenges through targeted government incentives, workforce upskilling programs, enhanced cybersecurity frameworks, and stronger organizational support is essential to promote AI integration. The findings provide valuable insights for policymakers, industry practitioners, and manufacturing firms in developing effective strategies to accelerate AI adoption and improve logistics performance in Malacca's manufacturing sector.

1. Introduction

Artificial Intelligence (AI) has become a transformative technology in logistics and supply chain management globally, offering capabilities such as intelligent decision-making, real-time route optimization, predictive analytics, and warehouse automation (Wamba *et al*., 2015). By integrating AI into logistics operations, companies can enhance delivery performance, reduce operational costs, and improve visibility across the supply chain (Fatorachian, 2024). Leading companies such as Amazon, DHL, Maersk, Walmart, and UPS have successfully applied AI to optimize resource allocation, streamline operations, and improve customer satisfaction, demonstrating AI's potential to enhance competitiveness worldwide (DocShipper, 2025). In Malaysia, AI adoption in logistics is growing steadily, driven by the government's Industry 4.0 and digital economy initiatives (MIDA, 2024). The manufacturing sector plays a critical role in Malacca's economy, generating jobs and attracting foreign investment (Bernama, 2020). To remain competitive in a rapidly changing global market, Malaysian manufacturers must adopt advanced technologies such as AI to enhance productivity and resilience (Md Fauzi Ahmad *et al*., 2022). However, the adoption of AI in logistics remains limited, particularly among small and medium-sized enterprises (SMEs), due to high investment costs, low digital readiness, and resistance to organizational change (Md Fauzi Ahmad *et al*., 2022).

AI has proven to create smarter, data-driven, and more efficient supply chains that enhance sustainability, reduce costs, and improve operational visibility, transforming logistics globally and in Malaysia (Hlatshwayo, 2023). While supportive government initiatives and industry investments provide a conducive environment, financial, technical, and talent-related barriers must be addressed for successful adoption (Shahril, 2023). As AI technologies continue to advance, their integration into manufacturing logistics becomes increasingly critical to maintaining competitiveness in a complex global market (Elliot, 2025). Nevertheless, limited empirical research has investigated the specific obstacles to AI adoption in Malacca's manufacturing logistics sector (Md Fauzi Ahmad *et al*., 2022).

In Malacca, logistics management faces multiple challenges including cybersecurity threats, data privacy concerns, high operational costs, and internal resistance to change (Noorbaiti Mahusin *et al*., 2024; Meng & Ahmad, 2024). These issues hinder effective AI integration and overall logistics performance. Studies on AI adoption in logistics management have highlighted empirical and practical gaps, with limited research focusing on Malaysia's manufacturing sector and few practical strategies tailored to local barriers (Ghani *et al*., 2022; Rahim *et al*., 2024; Sivanesan Tamil Selvam Tc, 2025; Clowes, 2024). Addressing these gaps is crucial to facilitate successful AI adoption and improve logistics efficiency in Malacca's manufacturing industry.

Therefore, this study aims to examine the barriers hindering AI adoption in logistics management within Malacca's manufacturing industry, focusing on internal resistance to organizational change, cybersecurity and data privacy concerns, and costs. Understanding these barriers will provide insights for policymakers, industry practitioners, and manufacturing companies to develop strategies that enable effective AI integration, strengthen logistics performance, and enhance regional competitiveness (Bernama, 2025). By evaluating the level of AI adoption and the relationship between identified barriers and implementation, this research contributes to a deeper understanding of the challenges and practical solutions needed to leverage AI in Malacca's manufacturing logistics sector (Dun & Bradstreet, 2024).

2. Literature Review

2.1 Logistic Management

Logistics Management Logistics management plays a significant role in manufacturing companies because it coordinates the flow of resources, information, and materials from suppliers to customers to ensure timely and cost-effective delivery (Chua *et al*., 2025). Effective logistics management practices have a direct on competitiveness operational performance, particularly in manufacturing SMEs where logistics costs can significantly impact profitability (Chua *et al*., 2025).

In Malaysia, logistics management faces challenges include inefficient costing procedures, which frequently result in suboptimal decision-making and increased expenses (Chua *et al*., 2025). Additionally, collaboration and information sharing between supply chain partners are essential in determining logistics efficiency since joint decision-making helps mitigate risks and improve responsiveness (Rose, 2015). Strategic planning and leadership commitment are also essential for improving logistics performance as effective management promotes the adoption of best practices and innovation within logistics operations (Mohamad *et al*., 2023).

However, Malaysian logistics companies frequently face obstacles that prevent the adoption of AI. For example, poor infrastructure, lack of skilled workforce, and resistance to change, which hinder the implementation of AI (Mohamad *et al*., 2023). Furthermore, the purchasing and logistics management must also be strategically aligned to optimize logistics performance; nevertheless, misalignment will lead to delays and inefficiencies (Chandran *et al*., 2024). In the context of manufacturing companies in Malacca, these logistics management challenges exacerbate the barriers to AI adoption, as companies struggle to balance cost control, process optimization, and technology innovation (Chua *et al*., 2025). Therefore, resolving these logistics management concerns is essential to getting over barriers to AI adoption and creating a long-term competitive edge in Malaysia's manufacturing industry (Rose, 2015).

2.2 AI in Logistic Management

Artificial Intelligence (AI) is transforming supply chain management and logistics by enabling innovative approaches such as automation, robotics, and intelligent transportation systems that were previously unattainable (Burnham, 2024; Managewp, 2024). The growing demand for faster, consumer-focused shipping, inventory management, and delivery services has further accelerated the adoption of AI in logistics operations (Didast *et al*., 2024). AI applications, including demand forecasting, pricing strategies, predictive maintenance, and route optimization, allow logistics decisions to become more adaptive and demand-driven (Lindquist, 2024).

Advancements in AI technology and declining implementation costs have provided logistics platforms with large-scale data processing and storage capabilities, improving operational efficiency (Firouzi *et al*., 2021). AI-powered forecasting and route optimization have enabled companies such as PepsiCo, Unilever, and FedEx to reduce inventory buffers, fuel consumption, and delivery delays while improving service reliability (Managewp, 2024; Bandeira, 2024). The integration of AI with Internet of Things (IoT) technologies further enhance logistics performance through real-time monitoring, predictive maintenance, and intelligent freight management (SandTech, 2025).

AI also strengthens risk management, warehouse operations, and customer service by detecting supply chain disruptions, improving order fulfillment accuracy, and automating customer interactions, which reduces operational costs and increases satisfaction (Dilmegani, 2020; SandTech, 2025). The transparency and real-time data sharing enabled by AI systems enhance collaboration among supply chain partners and improve overall resilience (Floship, 2024). As AI continues to evolve, its role in logistics management will expand further, positioning AI as a core driver of efficiency, scalability, sustainability, and customer-centric supply chains worldwide (McFarland, 2024; Burnham, 2024).

2.2.1 Demand Forecasting

Demand forecasting plays a critical role in effective supply chain management by enabling organizations to anticipate customer demand and make informed decisions related to inventory planning, procurement, and distribution (Daios *et al*., 2025). Advanced machine learning techniques such as neural networks, support vector machines, decision trees, gradient boosting, and long short-term memory models enhance forecasting accuracy by leveraging data-driven insights to support dynamic inventory and demand planning (Abaku *et al*., 2024; Daios *et al*., 2025). Artificial intelligence approaches, including artificial neural networks, data mining, and fuzzy models, are widely applied in supply chain management to predict customer consumption patterns and manage demand variability (Toorajipour *et al*., 2021).

Traditional demand forecasting methods rely heavily on historical data, which presents challenges when forecasting demand for new products or services with limited past records (Min, 2010). In such situations, AI tools such as sales projection models and social media sentiment analysis provide valuable insights into customer behavior, enabling firms to identify emerging markets and estimate future profitability more effectively (Kyriakos Skoularikis *et al*., 2021; Khatua *et al*., 2021). Studies have shown that neural networks and large language models significantly improve forecasting accuracy, particularly in environments characterized by irregular demand, thereby reducing economic costs and improving inventory performance (Amirkolaii *et al*., 2017; Krishnamoorthy *et al*., 2024).

AI-driven demand forecasting also supports workforce optimization by predicting logistics volumes, which helps reduce overtime costs and avoid under- or over-staffing (Flaviane *et al*., 2024). Practical applications, such as DHL's use of machine learning models combined with real-time economic and geopolitical data, demonstrate how AI enables continuous forecast updates, proactive resource allocation, and improved operational efficiency (Facey, 2023).

2.2.2 Route Optimization

AI-driven route optimization significantly enhances logistics efficiency by identifying the most effective delivery routes through the analysis of historical and real-time data such as traffic conditions, weather patterns, vehicle load, and delivery constraints (Reeve, 2025). Practical implementations, such as FedEx's AI-powered route planning system, demonstrate substantial benefits, including a reduction of 700,000 miles in daily delivery distance, resulting in fuel savings, lower carbon emissions, and improved on-time delivery performance (managewp, 2024).

By dynamically adjusting routes in response to real-world disruptions such as traffic congestion and accidents, AI algorithms help logistics companies maintain service reliability and maximize fleet utilization (Reeve, 2025). AI-based route optimization is particularly impactful in last-mile delivery, where studies report improvements of up to 40% in driver productivity and reductions of approximately 20% in fuel consumption (Reeve, 2025). These improvements not only reduce operational costs but also support environmental sustainability by lowering carbon footprints and minimizing unnecessary vehicle idling (Saxena, 2025).

Furthermore, AI-powered route optimization facilitates efficient multi-modal logistics by coordinating multiple warehouses and transportation modes to ensure cost-effective and timely deliveries (Saxena, 2025). The continuous learning capability of AI models allows them to adapt to changing traffic patterns and delivery conditions over time, leading to increased productivity and enhanced customer satisfaction (Saxena, 2025).

2.3 Barriers to AI Adoption

Artificial Intelligence (AI) has been widely recognized as a transformative technology that is reshaping supply chain management and playing a crucial role in the development of modern supply networks (Nitsche *et al*., 2021). Previous studies highlight how digital technologies such as the Internet of Things (IoT), advanced analytics, and AI have significantly influenced logistics operations by improving productivity and supporting strategic decision-making (Nitsche *et al*., 2021). The integration of AI technologies, including machine learning, predictive analytics, and autonomous systems, has demonstrated strong potential in enhancing supply chain efficiency, streamlining logistics processes, and improving demand forecasting, enabling firms to remain competitive in dynamic business environments (Kama & Lalla, 2024).

Research adopting a system thinking approach further emphasizes that AI enhances supply chain networks by strengthening knowledge capabilities, predictive functions, and automated decision-making processes (Baryannis *et al*., 2019). Despite these advantages, studies consistently identify internal resistance to change, cybersecurity and data privacy concerns, and high costs as the most significant barriers to AI adoption in supply chains and logistics (Cooper, 2025). Internal resistance arises because AI implementation disrupts existing organizational cultures, workflows, and decision-making structures, often triggering concerns over job displacement and loss of managerial control among employees and leaders (Miller V & Scott-Briggs, 2025; Aljohani, 2023). Without effective leadership support and change management strategies, such resistance can hinder successful AI adoption despite its potential benefits (Anastasia, 2024).

Cybersecurity and data privacy concerns also represent critical barriers due to the data-intensive nature of AI systems, which rely on large volumes of sensitive operational, supplier, and customer information (Ahmad, 2025). The integration of AI with cloud platforms and IoT technologies further increases exposure to cyber threats, raising concerns about data breaches and regulatory non-compliance (Tarihal *et al*., 2024). In addition, high implementation costs remain a practical constraint, particularly for small and medium-sized enterprises, as AI adoption requires substantial investment in infrastructure, software, skilled personnel, and ongoing system maintenance (Patil, 2025). Uncertainty surrounding return on investment further intensifies hesitation among decision-makers, limiting the scale and pace of AI adoption in logistics and supply chain operations (Miller V & Scott-Briggs, 2025).

2.3.1 Internal Resistance to Organizational Change

Internal resistance to organizational change is consistently identified as a major barrier to the adoption of Artificial Intelligence (AI) in logistics and supply chain management, largely due to employees' fears of job displacement and scepticism toward AI benefits (Rane *et al*., 2024). Resistance to change commonly arises from uncertainty, habituation, concerns over personal loss, and the belief that organizational changes may not serve employees' interests (Robbins *et al*., 2018). Employees often worry about their future roles, the real value of AI, and the possibility of losing employment, which can result in passive resistance or active opposition to AI initiatives (Rane *et al*., 2024).

Uncertainty plays a central role in resistance, as organizational change replaces familiar processes with unknown systems, generating discomfort and anxiety among employees (Robbins *et al*., 2018). Many workers fear that AI systems may surpass human cognitive and decision-making capabilities, threatening their professional autonomy and relevance, particularly in logistics-related roles that involve forecasting, optimization, and operational planning (Floridi *et al*., 2018). Although AI is designed to support rather than replace human labour, its perceived threat often overshadows its intended benefits (Rane *et al*., 2024).

Additionally, the automation of routine tasks through AI raises concerns about job insecurity, especially among lower-skilled workers whose roles are more vulnerable to technological replacement, potentially leading to social and economic tensions within organizations (Tong Su *et al*., 2025). Fear of personal loss, including reduced income, diminished status, or limited career progression, further intensifies cultural resistance to AI adoption (Robbins *et al*., 2018). Such resistance may manifest through reduced cooperation, non-compliance, or even deliberate obstruction of AI implementation efforts (Dufresne *et al*., 2021).

Resistance to AI adoption can significantly slow digital transformation initiatives, increase implementation costs, and lower return on investment by delaying deployment and restricting effective use of AI capabilities (Dufresne *et al*., 2021). Therefore, comprehensive change management strategies that address the social, cognitive, and emotional dimensions of resistance, such as transparent communication, employee involvement, and targeted training are essential to overcoming this barrier (Robbins *et al*., 2018).

2.3.2 Cybersecurity and Data Privacy Concerns

Cybersecurity and data privacy concerns are widely recognized as significant barriers to the adoption of artificial intelligence (AI), particularly in data-intensive sectors such as manufacturing and logistics (Muhammad Mudassir, 2024). AI systems rely on large volumes of sensitive operational, intellectual property, and personal data, which raises complex issues related to data ownership, privacy, and protection (Corallo *et al*., 2021). In manufacturing environments, IoT devices installed on factory floors generate critical data on production processes, material usage, and equipment conditions, but increased connectivity simultaneously expands the cyberattack surface and heightens security risks (Corallo *et al*., 2021).

The growing interconnectivity required for AI deployment has contributed to a sharp rise in cyberattacks targeting industrial systems, with 1,607 confirmed data breaches reported globally in industrial facilities in 2025, nearly double the previous year (Freestone, 2025). A substantial proportion of these breaches stemmed from vulnerabilities in third-party access and excessive system privileges, leading to severe operational disruptions, financial losses, intellectual property theft, and erosion of competitive advantage (Freestone, 2025). As a result, organizations are compelled to invest in advanced cybersecurity infrastructures, increasing implementation complexity and costs and further discouraging AI adoption (Assesfa, 2024).

Data privacy concerns further complicate AI integration, as organizations must comply with stringent regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), which govern the collection, storage, and processing of sensitive data (Grant Thornton Ireland, 2024). AI models often require access to large datasets containing personally identifiable information, increasing the risk of unintended data exposure if anonymization and consent mechanisms are inadequate (Saxena, 2024). Failure to address these issues can result in regulatory penalties, reputational damage, and loss of stakeholder trust (Saxena, 2024).

Additionally, the opaque nature of many AI algorithms creates further cybersecurity challenges, as "black-box" decision-making makes it difficult for security teams to detect data manipulation or poisoning attacks (Jada & Mayayise, 2023). These risks are compounded by the presence of shadow data outside formal governance frameworks, which may be unintentionally accessed and processed by AI systems, increasing exposure to cyber threats (Freestone, 2025). Consequently, cybersecurity and data privacy risks undermine trust between organizations and AI technology providers, slowing adoption and limiting data sharing essential for effective AI performance (Pennekamp *et al*., 2023; Brohan, 2024).

Overall, cybersecurity and data privacy issues remain among the most critical obstacles to AI adoption in industries that manage sensitive data, highlighting the need for robust data governance frameworks, strong security architectures, transparent AI models, and comprehensive third-party risk management to enable secure and trusted AI integration (Brohan, 2024; Freestone, 2025).

2.3.3 Costs

Financial constraints are a major barrier for organizations seeking to expand capabilities through advanced equipment, infrastructure, and innovative processes (Theorin *et al*., 2016). Companies often struggle to fund initial AI investments, including software, hardware, and data management systems (Khimanych, 2024). The competition for skilled AI and supply chain professionals further increases recruitment and compensation costs, adding to the financial burden (Khimanych, 2024).

The high perceived cost of ownership can negatively influence top management decisions regarding AI adoption, as implementing new technology often requires significant investment (Paul *et al*., 2021). Costs rise due to technology acquisition, integration with legacy systems, personnel training, and ongoing maintenance (Lucidworks, 2025). Recent data indicate that expenses for generative AI systems can reach $190,000 or more, prompting many manufacturers to adopt cautious, strategic investment approaches (Lucidworks, 2025).
Complexities in implementation such as ensuring system compatibility, meeting cybersecurity standards, and verifying AI outputs also contribute to unanticipated expenses (Lucidworks, 2025). Organizations therefore prioritize long-term benefits over rapid growth when planning AI adoption (Lucidworks, 2025). In addition, rising costs of recruiting and retaining qualified AI and supply chain specialists further increase total implementation expenses and timelines (Khimanych, 2024).

Despite these financial challenges, manufacturers continue to invest in AI due to its potential to improve productivity, reduce operational costs, and enhance efficiency, particularly in supply chain optimization, predictive maintenance, and quality assurance (Group, 2025). However, the initial financial commitment remains a key barrier that must be addressed to realize these benefits (Miller & Scott-Briggs, 2025). In conclusion, cost encompasses not only technology acquisition but also talent recruitment, system integration, training, and ongoing maintenance. These financial demands, uncertain return on investment, and implementation complexities make cost a significant barrier to AI adoption in industrial and logistics sectors (Klubnikin, 2021).

2.4 Research Framework

Fig. 1 below shows the conceptual framework for the relationship between barriers and AI adoption in logistics management. The independent variable is barriers adoption and dependent variable is AI adoption in logistics management.

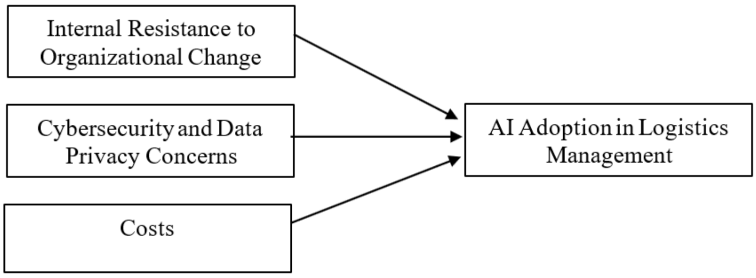

Fig. 1 *Research Framework*

3. Research Methodology

This study used a quantitative approach through survey research to gather data of the research. This approach enables researchers to objectively assess impact of specific barriers such as internal resistance to organizational change, cybersecurity and data privacy concerns, and costs using a large sample of manufacturing companies in Malacca (Azman *et al*., 2024). Population and Sampling

According to Dun & Bradstreet (2024), there are roughly 1,176 manufacturing companies in Melaka and using a sample size calculator, the appropriate population size is 290 manufacturing companies must be surveyed to ensure reliability and validity of the study. The potential respondent for each company includes logistics managers, IT manager, and supply chain manager. The size of the sample in this study was established by consulting the Krejcie and Morgan table (Krejcie and Morgan, 1970).

For this study, a non-probability approach, specifically purposive sampling was employed (Vehovar, 2016). Purposive sampling allows researchers to intentionally select individuals with specific attributes relevant to the study (Heath, 2023). This method is widely used across research paradigms because it enables the selection of high-quality samples that align precisely with the research questions (Stewart, 2024). By focusing on participants who meet predefined criteria, purposive sampling reduces sampling bias and enhances the reliability and credibility of the findings (Campbell *et al*., 2020; Nikolopoulou, 2023). This approach ensures that the collected data is both relevant and representative of the key characteristics being studied, improving the validity of the study outcomes (Campbell *et al*., 2020).

Primary data was first-hand information collected by researchers to address a research question or problem. It was gathered through methods like experiments, questionnaires, interviews, surveys, or observation. This study used primary data to examine barriers to AI adoption in logistics management in manufacturing companies in Malacca, Malaysia. Respondents were given questionnaires distributed via email or online platforms to obtain relevant information and achieve the research objectives. The questionnaire used in the survey consists of three sections, as shown in Table 1. The evaluation for Section B and C will be using a 5-point scale.

Table 1 *Questionnaire Instrument*

Section	Variables	Sources
Section A	Demographic	-
Section B	Barriers	Cooper (2025) Omar *et al*., (2022)
Section C	AI adoption in Logistics Management	Muhsin & Sara (2024)

The quantitative data collected were analyzed using SPSS version 27. The raw data were first checked for completeness, screened, and cleaned to ensure accuracy. Descriptive statistical analysis was then conducted to summarize respondents' profiles and key study variables using measures such as mean, standard deviation, frequency, and percentage. Normality tests, including the Kolmogorov-Smirnov and Shapiro-Wilk tests, were performed to assess whether the data followed a normal distribution and to confirm the suitability of subsequent statistical analyses. Reliability analysis was carried out using Cronbach's Alpha to evaluate the internal consistency of the measurement scales, with values of 0.60 or above indicating acceptable reliability. Finally, correlation analysis was conducted to examine the relationships between the identified barriers and AI adoption in logistics management, with the correlation coefficient used to determine the strength and direction of these relationships.

4. Results and Discussion

4.1 Response Rate

The respondents selected for this research were among the manufacturing companies in Malacca, Malaysia. A total of 290 respondents were required to answer the questionnaire for this study but only 155 respondents answered the questionnaires with 53.45% response rate.

4.2 Reliability Analysis of Pilot Study and Actual Study

Table 2 shows the results for pilot test that consists of Cronbach's Alpha values that was conducted for 30 respondents. The Cronbach's Alpha values for independent variables and dependent variables show the values between 0.7 – 1.0 which is 0.785 for Internal Resistance to Organizational Change, 0.789 for Cybersecurity and Data Privacy Concerns, costs for 0.780 and 0.898 for AI adoption. The values indicated that the research questionnaire is at a good level.

Table 2 *Reliability test for Pilot Study and Actual Study*

Variables	Pilot Study (30)		Actual Study (155)	
	Cronbach's Alpha	Interpretation	Cronbach's Alpha	Interpretation
Internal Resistance to Organizational Change	0.785	Good	0.900	Excellent
Cybersecurity and Data Privacy Concerns	0.789	Good	0.897	Good
Costs	0.780	Good	0.815	Good
AI adoption	0.898	Good	0.964	Excellent

Based on Table 2, the Cronbach's alpha results of the pilot study indicated good internal consistency for all variables. Internal resistance to organizational change showed a Cronbach's alpha coefficient of 0.785, cybersecurity and data privacy concerns recorded 0.789, and costs achieved 0.780, all indicating a good level of reliability. In addition, the dependent variable, AI adoption, demonstrated strong internal consistency with a Cronbach's alpha value of 0.898, reflecting a good level of reliability. In the actual study, the reliability values further improved. Internal resistance to organizational change showed excellent internal consistency with a Cronbach's alpha coefficient of 0.900. Cybersecurity and data privacy concerns recorded 0.897, while costs achieved 0.815, both indicating good levels of reliability. Moreover, AI adoption as the dependent variable achieved a Cronbach's alpha coefficient of 0.964, indicating an excellent level of internal consistency. Overall, the results from both the pilot and actual studies confirmed that all constructs in this research achieved acceptable to excellent reliability levels and were suitable for further statistical analysis.

4.3 Demographic Analysis

Table 3 shows the summary of demographic analysis. Based on the table, there are 14 questions in demographic information which consists of gender, age, race, education, job position, years of experience in logistics company, number of workers in logistics company and annual turnover of logistics company. Majority of the respondents are female with 54.8% while male with 45.2%. Most of the respondents are at the age of 21 to 30 years old with 44.5% and the highest race of the respondents are Chinese with 70.3%. Besides, majority respondents are from logistics department with 43.2%. Most of the respondents are categorized as Executives/Officers with 30.3%, majority of the respondents had been employed for more than 5 years with 44.5% and the highest rate of the respondents are worked in the food and beverage sector with 36.8%. Moreover, majority of respondents are come from companies with more than 20 years of operation with 31.9%, most of the respondents were from local companies with 51% and the highest rate of company size was companies with 150-249 employees with 37.4% and the largest proportion of respondents came from companies with RM10-50 million. Furthermore, majority of respondents came from the companies focusing on the domestic market with 45.8%, the highest current status of AI is already been implemented with 67.1% and the most of the respondents were from Private Listed companies with 60.6%.

Table 3 *Summary of demographic analysis*

Demographic	Details	Frequency	Percentage (%)
Gender	Male	70	45.2
	Female	85	54.8
Age	21-30 years old	69	44.5

	31-40 years old	34	21.9
	41-50 years old	37	23.9
	51-60 years old	15	9.7
Race	Malay	29	18.7
	Chinese	109	70.3
	Indian	16	10.3
	Others	1	0.6
Department	Human Resource	21	13.5
	Procurement	10	11.65
	Logistics	67	43.2
	Quality Control	7	4.5
	Sales and Marketing	30	19.4
	Production/Manufacturing	12	7.7
	Others	8	5.2
Current Position in the Company	Top Management (CEO/Director/General Manager)	9	5.8
	Middle Management	35	22.6
	(Manager/Assistant Manager) Executive/Officer	47	30.3
	Supervisor/Team Leader	25	16.1
	Staff/Clerk/Operator	35	22.6
	Others	4	2.6
Number of years working in the company	1-3 years	59	38.1
	4-5 years	27	17.4
	5 years and above	69	44.5
Type of Industry	Furniture	7	4.5
	Food and Beverage	57	36.8
	Textiles	7	4.5
	Wood, paper, and printing	17	11
	Plastics and Rubber	27	17.4
	Electronics	40	25.8
Years of Operation	< 5 years	44	28.4
	5-10 years	15	9.7
	11-15 years	24	15.5
	16-20 years	21	13.5
	>20 years	51	32.9
Company Ownership Type	Local (domestic) company	79	51
	Multinational corporation (MNC)	72	46.5
	Joint Venture	4	2.6
Company Size	Jan-49	24	15.5
	50-149	48	31
	150-249	59	38.1
	250 and above	24	15.5
Annual Revenue/Turnover	< RM 10 million	38	24.5
	RM10 – 50 million	49	31.6
	RM51 – 100 million	35	22.6
	>RM100 million	33	21.3
Primary Market Served	Domestic (within Malaysia)	71	45.8
	Regional (ASEAN)	27	17.4
	International (Global)	57	36.8

Current Status of AI	Implemented	104	67.1
	Planning to implement within 1 – 2 years	35	22.6
	No current plans	16	10.3
Ownership Structure	Private Limited (Sdn. Bhd)	94	60.6
	Public Listed (Berhad)	43	27.7
	Government-linked company (GLC)	6	3.9
	Cooperative	11	7.1
	International Limited	1	0.6

4.4 Barriers to AI Adoption

Tables 4 indicates data analysis for key barriers such as internal resistance to organizational change, cybersecurity and data privacy concerns, and costs. For internal resistance to organizational change, it showed the highest mean value is the first question with the value of 4.40, which is employees have concerns about job loss related to the use of AI technologies in logistics management while the lowest mean is 4.26 with the question employees show resistance to changes related to AI technologies in logistics management. Besides, for cybersecurity and data privacy concerns, the highest mean value is 4.51 with the question cybersecurity risks exist in the use of AI technologies in logistics management while the lowest mean is 4.45 with the question data privacy is a concern in the use of AI technologies in logistics management. Furthermore, for costs, the highest mean is 4.52 with the question ongoing maintenance and upgrading of AI in logistics management require significant costs while the lowest mean is 4.01 with the question return on investment (ROI) of AI technologies in logistics management are limited.

Table 4 *Barriers to AI Adoption*

Statement	Mean	Interpretation
1) Internal Resistance to Organizational Change		
Employees have concerns about job loss related to the use of AI technologies in logistics management.	4.40	High
Employees show limited readiness for digital transformation in logistics management.	4.30	High
Organizational culture does not fully support innovation with AI technologies in logistics management.	4.29	High
Employees show resistance to changes related to AI technologies in logistics management.	4.26	High
Total Average	4.31	High
2) Cybersecurity and Data Privacy Concerns		
Data privacy is a concern in the use of AI technologies in logistics management.	4.45	High
Cybersecurity risks exist in the use of AI technologies in logistics management.	4.51	High
Sensitive logistics data can be exposed when AI technologies are applied.	4.46	High
Trust in technology providers regarding data security is limited.	4.50	High
Total Average	4.48	High
3) Costs		
AI in logistics management requires a high initial investment.	4.48	High
Return on investment (ROI) of AI in logistics management is uncertain.	4.01	High
Financial resources available for AI technologies in logistics management are limited.	4.39	High
Ongoing maintenance and upgrading of AI in logistics management require significant costs.	4.52	High
Total Average	4.35	High

4.5 AI adoption among Manufacturing Companies

Table 5 presents the analysis of AI adoption. Based on the table, the question that had highest mean value is the eighth question with the statement of “Real-time monitoring of logistics operations (e.g., live monitoring of warehouse equipment, loading/unloading progress, vehicle performance metrics)” with the value of 4.46 while the lowest mean value is 4.24 with the statement of " Transportation and distribution management (e.g., route optimization, fleet management, autonomous vehicles)".

Table 5 *AI Adoption among Manufacturing Companies*

Statement	Mean	Interpretation
Warehouse and storage operations (e.g., automated picking, robots, smart storage systems).	4.37	High
Transportation and distribution management (e.g., route optimization, fleet management, autonomous vehicles).	4.24	High
Inventory management (e.g., demand forecasting, stock optimization, automated counting).	4.45	High
Supply chain visibility and tracking (e.g., real-time monitoring, predictive alerts).	4.43	High
Customer service and order processing (e.g., chatbots, automated documentation).	4.43	High
Predictive maintenance of logistics equipment and vehicles.	4.34	High
Delivery optimization (e.g., scheduling, route planning, drones).	4.41	High
Real-time monitoring of logistics operations (e.g., live monitoring of warehouse equipment, loading/unloading progress, vehicle performance metrics).	4.46	High
Logistics planning and decision support systems (e.g., software or AI tools that help plan routes, allocate resources, or choose the best logistics strategies).	4.44	High
Digital twins or computer-based simulation models for logistics operations (e.g., a virtual model of a warehouse or transport network).	4.33	High
Total Average	4.39	High

Based on Table 6, the normality was analyzed on barriers and AI Adoption. The results showed that the data obtained for all of the variables are non-normal data under Kolmogorov-Smirnov[a] with the significance level is <.001 which is below 0.05.

Table 6 *Normality Test*

	Kolmogorov-Smirnov			Shapiro-Wilk		
Variable	Statistic	df	Sig.	Statistic	df	Sig.
Barriers	0.212	155	<.001	0.88	155	<.001
AI Adoption	0.201	155	<.001	0.806	155	<.001

4.6 Correlation Analysis

The Spearman's correlation analysis reveals strong and statistically significant positive relationships between the identified barriers and AI adoption in logistics management (Turney, 2022). Internal resistance to organizational change shows a strong positive correlation with AI adoption ($r = 0.797$, $p < 0.001$), indicating that resistance significantly affects AI implementation (Stewart, 2023). Cybersecurity and data privacy concerns are also strongly correlated with AI adoption ($r = 0.752$, $p < 0.001$), highlighting the influence of security-related risks on adoption decisions (McClenaghan, 2024). Similarly, costs demonstrate a strong positive relationship with AI adoption ($r = 0.733$, $p < 0.001$), suggesting that financial constraints play an important role in AI adoption (Turney, 2022). Overall, these coefficients fall within the strong association range, supporting the study's hypotheses (Stewart, 2023).

Table 7 *Correlation Analysis*

Spearman's Rho		Internal Resistance to Organizational Change	Cybersecurity and Data Privacy Concerns	Costs	AI adoption
AI Adoption	Measure	Value	Value	Value	Value
AI Adoption	Correlation Coefficient	.797**	.752**	.733**	1.000
	Sig. (2-tailed)	<.001	<.001	<.001	.

This study examined the level of AI adoption in logistics management among manufacturing companies in Malacca using descriptive analysis and found that overall adoption was high, with an average mean score of 4.39, indicating strong agreement that AI was widely applied across logistics functions, consistent with prior studies on AI-driven logistics efficiency (Kama & Lalla, 2024). Real-time monitoring recorded the highest adoption level (mean = 4.46), followed by inventory management (mean = 4.45) and logistics planning and decision support systems (mean = 4.44), reflecting organizations' emphasis on visibility, forecasting accuracy, and decision- making efficiency, as supported by existing literature (Bendhi, 2025; Tadayonrad & Ndiaye, 2023). High adoption was also observed in supply chain visibility, customer service, delivery optimization, warehouse operations, and predictive maintenance (means ranging from 4.34 to 4.43), aligning with studies highlighting AI's role in enhancing coordination, automation, and cost reduction in logistics (Chen *et al*., 2021; Dwivedi & Dey, 2025). Although transportation and distribution management recorded the lowest mean score (mean = 4.24), it remained within the high adoption category, suggesting that advanced AI applications face relatively slower adoption due to complexity and resource constraints, as noted in previous research (Akter *et al*., 2025). Overall, the findings confirmed that AI adoption in logistics management was well established in Malacca's manufacturing sector, particularly in areas offering immediate operational benefits, consistent with existing literature on staged AI implementation strategies (Gonçalves & Domingues, 2025).

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Furthermore, this study examined the relationship between barriers and AI adoption in logistics management among manufacturing companies in Malacca using Spearman's rho correlation analysis due to non- normal data distribution. Internal resistance to organizational change had a strong positive correlation with AI adoption, suggesting that concerns over job security, limited digital readiness, and resistance to change were experienced more in organizations actively adopting AI, driven by the long-term strategic benefits of digital transformation (Cieslak & Valor, 2024; Vial, 2019; Raisch & Krakowski, 2020; Uren & Edwards, 2023; Chhatre, 2024). Cybersecurity and data privacy concerns also showed a strong positive relationship, indicating heightened awareness of data risks as AI adoption increased, while organizations perceived the long-term value of AI to outweigh these challenges (Gracias & Kinton, 2024; None Mikhalov Alojo, 2024; Admass *et al*., 2024; Vial, 2019; Raisch & Krakowski, 2020). Costs similarly demonstrated a strong positive correlation, reflecting that higher adoption involved greater investment and maintenance costs, justified by the strategic and operational benefits of AI (Ayinaddis, 2025; Raftopoulos & Juho Hamari, 2024; Vial, 2019; Raisch & Krakowski, 2020). Overall, the findings indicated that although barriers existed, AI adoption increased as organizations managed resistance, cybersecurity, and financial challenges effectively, highlighting the importance of a holistic approach integrating change management, technological safeguards, and financial planning to support successful AI adoption (Vial, 2019; Raisch & Krakowski, 2020).

5. Conclusion

This study examined the relationship between key barriers, namely internal resistance to organizational change, cybersecurity and data privacy concerns, and costs, and AI adoption in logistics management among manufacturing companies in Malacca, Malaysia. The findings from Spearman's correlation analysis revealed strong positive relationships between all three barriers and AI adoption. Although these factors are commonly viewed as challenges, the results suggest that higher levels of organizational readiness, awareness, and strategic commitment enable companies to adopt AI successfully. The study highlights the importance of effectively managing internal resistance, strengthening cybersecurity and data privacy frameworks, and planning financial resources carefully to support sustainable AI implementation in logistics management.

Despite the meaningful findings, several limitations were identified. The study focused only on manufacturing companies in Malacca, which limits the generalizability of the results to other regions or industries. In addition, the data were collected within a limited time frame and may not fully reflect long-term trends in AI adoption, especially as the manufacturing sector continues to evolve due to technological, economic, and regulatory changes. Furthermore, the study employed a quantitative approach using questionnaires, which may not have fully captured deeper qualitative insights into organizational and employee perspectives regarding AI adoption.

Based on these findings and limitations, several recommendations are proposed. Practitioners should develop comprehensive financial strategies that consider both implementation costs and long-term value, establish strong cybersecurity and data privacy measures, and address internal resistance through employee training and by fostering a culture of innovation. Organizations are also encouraged to align AI initiatives with strategic goals and prioritize applications that offer immediate operational benefits, such as real-time monitoring, inventory management, and decision support systems. Future researchers are recommended to adopt qualitative or mixed-method approaches, expand the study to other regions and industries, and explore the influence of organizational culture on AI adoption. Overall, this study provides valuable guidance for overcoming barriers and enhancing AI adoption in logistics management within the manufacturing sector.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Tan Zen Nie and Wan Karimah Wan Ahmad;* ***data collection:*** *Tan Zen Nie and Wan Karimah Wan Ahmad;* ***analysis and interpretation of results:*** *Tan Zen Nie and Wan Karimah Wan Ahmad;* ***draft manuscript preparation:*** *Tan Zen Nie and Wan Karimah Wan Ahmad. All authors reviewed the results and approved the final version of the manuscript.*
conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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