READINESS FOR ARTIFICIAL INTELLIGENT ADOPTION IN SUSTAINABLE SUPPLY CHAIN IN THE MALAYSIAN LOGISTICS INDUSTRY

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ABSTRACT

This study examines the readiness of the Malaysian logistics industry to adopt Artificial Intelligence (AI) to enhance sustainable supply chain performance. The rapid evolution of global supply chains and increasing sustainability pressures underscore the need for digital transformation. This research, guided by the Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory, investigates key determinants affecting AI adoption supply chain complexity, technological readiness, top management support, and sustainability goals. Using a quantitative research design, data were collected through structured questionnaires from 211 managerial-level employees in Malaysian logistics companies. The analysis, conducted using SPSS, includes descriptive statistics, correlation, and multiple regression tests to explore the relationships between these determinants and AI adoption. Results indicate that while the logistics industry exhibits high readiness in terms of technological infrastructure and sustainability goals, AI adoption remains moderate. The study highlights that supply chain complexity and technological readiness are significant predictors of AI adoption, while top management support plays a crucial role in facilitating successful implementation. The findings suggest that while Malaysian logistics companies are prepared to implement AI, there is a gap between intent and full-scale adoption. The paper contributes to both theoretical knowledge on AI adoption in developing economies and practical insights for policy makers and industry leaders to drive digital transformation and sustainability in logistics. Future research should explore long-term AI impacts and extend the study across different sectors.

Keywords: Artificial Intelligence Adoption, Supply Chain Complexity, Technological Readiness, Sustainable Goals, Top Management Support

ABSTRAK

Kajian ini mengkaji kesediaan industri logistik Malaysia untuk mengguna pakai Kecerdasan Buatan (AI) untuk meningkatkan prestasi rantaian bekalan yang mampan. Evolusi pesat rantaian bekalan global dan tekanan kemampanan yang semakin meningkat menggariskan keperluan untuk transformasi digital. Penyelidikan ini, berpandukan rangka kerja Teknologi-Organisasi-Alam Sekitar (TOE) dan teori Resapan Inovasi (DOI), menyiasat penentu utama yang mempengaruhi penggunaan AI: kerumitan rantaian bekalan, kesediaan teknologi, sokongan pengurusan atasan dan matlamat kemampanan. Menggunakan reka bentuk penyelidikan kuantitatif, data dikumpul melalui soal selidik berstruktur daripada 211 pekerja peringkat pengurusan di syarikat logistik Malaysia. Analisis, yang dijalankan menggunakan SPSS, termasuk statistik deskriptif, korelasi dan ujian regresi berbilang untuk meneroka hubungan antara penentu ini dan penggunaan AI. Keputusan menunjukkan bahawa walaupun industri logistik mempamerkan kesediaan yang tinggi dari segi infrastruktur teknologi dan matlamat kemampanan, penggunaan AI kekal sederhana. Kajian itu menyerlahkan bahawa kerumitan rantaian bekalan dan kesediaan teknologi adalah peramal penting penggunaan AI, manakala sokongan pengurusan atasan memainkan peranan penting dalam memudahkan pelaksanaan yang berjaya. Penemuan menunjukkan bahawa walaupun syarikat logistik Malaysia bersedia untuk melaksanakan AI, terdapat jurang antara niat dan penggunaan berskala penuh. Kertas kerja ini menyumbang kepada kedua-dua pengetahuan teori tentang penggunaan AI dalam ekonomi membangun dan cerapan praktikal untuk penggubal dasar dan pemimpin industri untuk memacu transformasi digital dan kemampanan dalam logistik. Penyelidikan masa depan harus meneroka kesan AI jangka panjang dan memperluaskan kajian merentasi sektor yang berbeza.

Kata kunci: Penggunaan Kecerdasan Buatan, Kerumitan Rantaian Bekalan, Kesediaan Teknologi, Matlamat Mampan, Sokongan Pengurusan Tertinggi

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"In the name of Allah, the Most Gracious, the Most Merciful"

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List of Abbreviation

AI	Artificial Intelligence
SSC	Sustainable Supply Chain
SCC	Supply Chain Complexity
TR	Technological Readiness
TMS	Top Management Support
SG	Sustainable Goals
SDG	Sustainable Development Goals
TOE	Technology Organization Environment
DOI	Diffusion of Innovation
SPSS	Statistical Package for the Social Science

CHAPTER ONE

1.0 Background of the study

The introduction of Artificial Intelligence (AI) in the supply chain management has become a driver of transformational shift, particularly towards the cultivation of sustainable logistic practices at the global and regional levels in Malaysia. Sustainable supply chains aim to strike the balance between economic efficiency and environmental and social responsibilities and AI technologies, including predictive analytics, machine learning, automation, and data-driven decision-making are playing a critical role in achieving the goals (indravathy & abd rahim, 2024). The use of AI allows companies to plan routes optimally, control inventory, forecast demand, and reduce emissions, which will be reflected in the increase in operational efficiency and reduced ecological footprint. The logistics Industry in Malaysia is an important segment that connects local production to the global markets and has a substantial share of the GDP in the country. However, the use of AI in the logistics of Malaysian companies is relatively low, despite the development of digital technologies, which is typically influenced by the absence of technological infrastructure, organizational culture, a lack of technical skills, and doubt about the compliance with the regulations (Izzaty Roszelan & Shahrom, 2025).

The current literature on AI adoption in Malaysian supply chains mainly concentrates on retail areas, where AI functions are discussed in terms of inventory smartness, demand prediction, and optimization of procurement (Macron, 2025) points to the role of AI-based demand forecasting to increase the accuracy of inventory and lower the costs of retail logistics, but these observations have not been thoroughly investigated in the context of larger logistical issues including multi-modal transport, warehousing, and international trade. In addition, challenges, including data quality concerns, the complexity of integrating with the legacy systems, and the lack of clarity in government policies are highlighted (Yoo et al., 2018).This implies a significant gap in knowledge about the readiness factors that impact the capacity of Malaysian logistics companies to implement AI technologies in the quest to attain the sustainable objectives. Other than technological preparedness, organizational and environmental aspects play a vital role in determining the results of AI adoption. The strategic frameworks state government policies like the Digital Economy Blueprint in Malaysia and the National AI Roadmap have provided incentives to encourage digital innovation and capacity building by outlining the strategic frameworks to enhance the use of AI in industries (Unit, 2021). However, studies state that although the governmental support is a positive factor, firm-specific elements, including leadership commitment, organizational culture that promotes innovation, and resource availability are also critical (Izzaty Roszelan & Shahrom, 2025).

Moreover, the challenges that logistics markets in regions may face put businesses in fierce competition, which forces them to be more responsive and efficient, which in turn encourages the adoption of AI despite the underlying issues. However, most Malaysian logistics Industry are still in the initial implementation phase, and empirical research of the multidimensional preparedness -technological, organizational, and environmental -that affects the practical application of AI in the field is needed. The theoretical basis of the proposed research is based on two widely held frameworks that describe technology adoption dynamics, namely: Technology-Organization-Environment (TOE) framework, and the Diffusion of Innovation (DOI) theory. According to the description offered by Tornatzky and Fleischer (1990), TOE framework describes that the use of new technology in an organization is affected by three contexts, which encompass technological and organizational, as well as environmental. The technological context relates to the nature of the innovation which is its availability, complexity and compatibility with the existing systems. Organizational context involves a set of internal characteristics like the size of a firm, headquarter culture, managerial support and capability of a firm. The environmental context is used as the external forces, which find their origin in the industry competition, the regulatory environment, and the norms of the society (Baker, 2011). TOE provides a holistic prism through which to discuss both internal and external enablers or hindrances of AI preparedness in the local logistics companies of Malaysia. In line with TOE, the theory of Diffusion of Innovation (DOI) that Rogers, (2003) formulated elucidates the way in which innovations spread across social systems overtime depending on channel of communication and attributes of adopters. DOI recognizes the five characteristics of innovation that impact the adoption rates: relative advantage benefits of a new practice compared to the previous one, compatibility, complexity, trialability, and observability visibility of results (drența & lobonțiu, 2020; rogers, 2003). DOI also differentiates adopters by innovator, early adopters, early majority, late majority and laggard to give insights about the timing of adoption and social influence behaviour. Whereas DOI generally focuses on the personal or organizational vision of innovation, it slightly neglects the environmental institutional pressures, which play a vital role in the field of regulation, such as in the logistics (Horani et al., 2023). Therefore, TOE and DOI theories are a sound choice of the theory to combine to study them. TOE guarantees consideration of both the organizational and environmental factors in addition to being able to provide a refined picture on the nature of innovations and uptake behavior, and DOI provides. With this combined method, the willingness of Malaysian logistics companies to adopt AI will be properly investigated to transform the supply chain into a sustainable one. Past research that has optioned TOE and DOI to the adoption of AI in supply chains has been shown to have complementary advantages in terms of their abilities to capture the complexity of technology diffusion and more so in emerging economies (Alka'awneh et al., n.d.2025).

Concisely, the current literature exposes both transformation potential of AI towards sustainable supply chain, as well as the significant knowledge gaps on the elements of readiness in the Malaysian logistics Industry. In this work, the combination of the TOE and DOI theoretical lenses will help fill this gap by addressing technological, organizational, and environmental aspects that affect the level of readiness to adopt AI. It is believed that the findings of this study can be useful to policy makers, industry players, and scholars as they could offer practical knowledge to enable successful integration of AI, eventually helping achieve the vision of a Malaysian digitally empowered, sustainable logistics industry.

1.1 Problem of Statement

The Malaysian logistics sector is experiencing increasing pressure to modernize to stay competitive, particularly as global supply chain disruptions have highlighted the inefficiencies of traditional logistics models. While AI offers significant potential to enhance the efficiency, accuracy, and sustainability of supply chain operations, its adoption within the Malaysian logistics industry remains limited. As the logistics industry plays a critical role in connecting local production to global markets, it faces mounting pressures to optimize operations while reducing environmental impacts and improving service delivery. However, despite the undeniable benefits of AI, such as enhancing demand forecasting, route optimization, and inventory management, the integration of AI technologies remains low across many logistics' firms in Malaysia

(Rahim et al., 2024). According to a report by AI Malaysia, although awareness of AI's potential is growing, approximately 84% of Malaysian companies are still in the early stages of AI adoption, particularly within the logistics sector, with most firms only exploring AI technologies rather than implementing them on a large scale (Ai Malaysia, 2025). This suggests a significant gap between technological readiness and full-scale adoption.

There are several barriers hindering the adoption of AI in the logistics sector. Technological readiness, including the lack of advanced digital infrastructure, skilled human resources, and integration capabilities, is a key obstacle. Many companies still operate with legacy systems that are not easily adaptable to new AI solutions, making the transition both challenging and costly (Indravathy & Abd Rahim, 2024). Moreover, cost concerns are another critical barrier, as the initial investment in AI technologies and the subsequent costs of training staff and upgrading systems are often prohibitive for smaller companies. Despite government incentives and grants aimed at facilitating digital transformation, such as those outlined in Malaysia's Industry 4.0 policy and Budget 2025, these financial constraints still deter widespread AI adoption (Mida, 2025). In addition, issues such as data silos and poor data quality further exacerbate the situation, making it difficult for firms to fully capitalize on AI's potential to drive operational efficiency (6wresearch, 2025).

Currently, the readiness level for AI adoption in Malaysia's logistics industry is moderate to high in terms of technological infrastructure, with certain regions, particularly Kuala Lumpur and Selangor, leading in AI integration (AI Malaysia, 2025). However, most logistics firms, particularly SMEs, are still in the early stages of adoption, with a significant portion of the industry still relying on traditional methods for key functions such as routing and demand forecasting. While AI adoption has been linked to improved operational efficiency, profitability, and sustainability, the reluctance to implement these technologies is creating a clear divide between companies that are advancing and those that are lagging (Culot et al., 2024). The lack of AI integration is not just about cost savings; it also affects the efficiency and performance of logistics operations, resulting in longer delivery times, higher operational costs, and missed sustainability targets (Rahim et al., 2024).

Government policies, such as the Digital Economy Blueprint and the National AI Roadmap, aim to accelerate AI adoption in Malaysia by providing incentives for digital infrastructure development and talent upskilling. However, despite these efforts, the gap between policy and actual implementation persists, as firms still face significant barriers in terms of capital investment, training, and the integration of AI solutions into existing systems (Mida, 2025). By identifying these challenges, this study aims to provide evidence that supports the need for more targeted interventions by policymakers to enhance AI adoption in the logistics sector. The findings will contribute valuable insights into how government policies could be refined to address the specific obstacles faced by logistics firms, ensuring a more effective and widespread adoption of AI technologies that can drive efficiency, sustainability, and competitiveness in the sector.

1.2 Research Questions:

This research focuses on the following questions:

1. What is the impact of supply chain complexity and technological readiness on the adoption of artificial intelligence in the Malaysian logistics industry?

2. How does top management support influence the adoption of artificial intelligence in logistics companies in Malaysia?
3. What is the effect of sustainable goals on the adoption of artificial intelligence within the Malaysian logistics industry?

1.3 Research Objectives

The researcher proposed the following objectives:

1. To examine the impact of supply chain complexity and technological readiness on the adoption of artificial intelligence in the Malaysian logistics industry.
2. To investigate the effect of top management support on artificial intelligence adoption among logistics companies in Malaysia.
3. To examine the influence of sustainable goals on the adoption of artificial intelligence in the Malaysian logistics industry.

1.4 Significance of the study

The value of the research is two-pronged, as it will apply both to the academic and the practical requirements in the Malaysian logistics market and beyond. Academically, the research has a very important knowledge gap in the literature because it deals with AI adoption in the Malaysian logistics industry, one of the areas that is under researched despite increased global interest in sustainable supply chain management and digital transformation. Combining Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory, the research contributes to the theoretical knowledge on the topic by observing the overall effect of technological capabilities, organizational dynamics, and environmental sustainability goals on the readiness to adopt AI. Such an all-encompassing strategy enhances academic literature with new models and empirical data that can be reused or modified to apply to other developing economies with comparable developmental and sustainability issues (Alka'awneh et al., 2025).

In practice, the research has a lot to contribute to various stakeholders of the Malaysian logistics ecosystem. The findings can help logistics companies to determine their levels of preparedness, detect the barriers that are critical, including the lack of technological infrastructures or the support of management, and work out specific strategies to adopt AI solutions that will increase the efficiency and sustainability of their operations. This is of particular importance considering that Malaysia strives to become a regional digital and green logistics hub under the national frameworks such as the Malaysia Digital Economy Blueprint 2021-2030, and the National AI Roadmap (Unit, 2021; Yoo et al., 2018). Also, the findings of this research can be used by policymakers and regulators of the industry to create better policies, incentives, and capacity-building programs that would solve industry-specific issues and increase the speed of sustainable AI implementation. The research can also be useful to technology providers and consultants as it points at areas of priority innovation and support that are specific to the needs of Malaysian logistics companies (Mohamed, 2023;Rahim et al., 2024).

All in all, the present research leads to a sustainable digital transformation process in the logistics of the Malaysian economy, as it allows it to address the emerging needs of the world to have cleaner and smarter supply chains. The recommendations (which are evidence-based) are also supposed to move towards increased economic competitiveness and, at the same time, promote better environmental stewardship and social responsibility, addressing global sustainability goals, including the United Nations Sustainable Development Goals (Ozili, 2025).

1.4.1 Theoretical Significance

The theoretical worth of the performed study can be linked to the addition to the breadth and the depth of the current stock of research on the application of AI to the sustainable supply chains, as well as to the impact that it has on the Malaysian environment of the logistics, which is relatively underrepresented in the literature. A conceptual framework of integrative approach has been presumed in this research with Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory integration to examine the multidimensional factors which may influence the willingness to embrace AI. It presents a bit of new knowledge of the interaction of technological capacity, organizational dynamics and environmental sustainability targets in the logistics Industry of a developing economy like Malaysia using these theories.

1.4.2 Practical Significance

The practical importance of the research is that it offers practical knowledge and recommendations to Malaysian logistics Industry interested in using AI to implement more sustainable supply chains. The study offers logistics managers with measures of overcoming barriers by highlighting some of the major factors that drive adoption of AI including technological readiness, supply chain complexity, top management support and sustainability goals. This aids in the enhancement of operational effectiveness, cost reduction, environmental performance minimization, and enhancement of supply chain resilience- aspects that are important in ensuring that a company remains competitive in the changing global market.

1.5 Scope of the Study

This research investigates the adoption of Artificial Intelligence (AI) in the Malaysian logistics industry, focusing specifically on its role in enhancing sustainable supply chain performance. The scope is confined to logistics companies operating within Malaysia, including both small-to-medium enterprises (SMEs) and large corporations engaged in transportation, warehousing, inventory management, and distribution. The study explores four key determinants of AI adoption based on the Technology-Organization-Environment (TOE) framework and Diffusion of Innovation (DOI) theory supply chain complexity, technological readiness, top management support, and sustainability goals. These factors have been identified as crucial to understanding the readiness of logistics firms in adopting AI technologies. The research will not extend to other sectors outside logistics or to industries unrelated to supply chain operations.

The target population for this study consists of logistics companies in Malaysia, with a sample of 211 managerial-level employees selected from companies involved in logistics operations. These respondents, including Assistant Managers, Supervisors, and Middle Managers, are chosen due to their direct involvement in decision-making regarding AI adoption, technological integration, and strategic operations. The research will use purposive sampling, focusing specifically on managers and decision-makers from the Association of Malaysian Hauliers (AMH),

The unit of analysis for this study is the individual level, focusing on the perceptions, experiences, and attitudes of these managerial respondents regarding the adoption of AI within their organizations. The data collected will provide insights into the factors influencing AI readiness, barriers to adoption, and the overall readiness of logistics firms in Malaysia to integrate AI into their supply chain operations. By using this approach, the research aims to align with the study's objectives of identifying and assessing the key determinants of AI adoption in the logistics industry.

1.6 Definition of key terms

The adoption Artificial intelligence (AI) in Supply Chain and Logistics:

AI is defined as technologies that allow machines to replicate the process of human intelligence, i.e. learn, reason and make decisions. In supply chains, AI is employed to optimize different processes: planning, manufacturing, logistics, and asset management, analysing masses of data to make processes more efficient, predictive, and responsive (Chenna, 2024; Rahi, 2025).The application of AI is machine learning models, predictive analytics, automation, and generative AI to optimize inventory handling, anticipate demand or supply, optimization of routes, and monitoring of supply chain in real-time.

Sustainable Supply Chain:

A sustainable supply chain combines economic, environment, and social goals to make sure that activities in the supply chain generate long-run value and reduce adverse effects of the supply chain activities on the environment and society (Katz, 2003). It focuses on minimizing energy use, emissions and waste, enhancing ethical labor, fairness and adherence to regulations. Sustainable supply chains are those that apply technologies, such as AI, to enhance transparency, monitoring of environmental indicators, and resource optimization. As an example, AI-enabled DHL systems find the optimal delivery route and used less fuel, dropping drastically the logistics carbon footprint (Nyamekeh et al., 2025). Supply chain sustainability is a key element that businesses must strive to achieve, to address the increasing regulatory pressures, also to satisfy the expectations of the stakeholders, and to improve their resilience.

Supply Chain Complexity:

The concept of supply chain complexity describes the degree of diversity and interconnectivity of a supply network, such as the number of sourcing companies, the geographic spread of the network, product differentiation, and operations (Rahim et al., 2024). The complexity is high and requires advanced capabilities of coordination and data control, which makes the use of AI more difficult and more valuable. Multifaceted supply chains result in extensive, diversified data sets in which AI could enhance decision-making responsiveness, like anticipating disruptions or maximizing inventory distribution across different places.

Technological Readiness:

Technological preparedness is the level at which organizations have the digital infrastructure, IT resources, and human resources to implement the latest technologies such as AI (Alam et al., 2025; Uren & Edwards, 2023). Companies, which are logistically prepared, have incorporated data systems, cloud computing, cybersecurity, and well-trained personnel trained in the use of AI tools. Greater preparedness is linked to an easier integration of AI and quicker ROI, as well as greater sustainability of adoption. To give an example, companies that have robust IT ecosystems can implement AI-based demand forecasting technologies that lower inventory expenses and prevent overstocking (indravathy & abd rahim, 2024).

Top Management Support:

Top management support refers to the proactive participation of leading management, willingness, and resource support of top management to promote AI adoption efforts (Mohamed, 2023). Leadership defines organizational priority, organizational culture, funding, and change management strategies that will be required to go through resistance and integrate AI into core processes. Effective AI projects, like the automated system of distribution of products to consumers of Nike, indicate well-established executive sponsorship in line with business strategy and innovation culture.

Sustainable Goals:

Sustainable goals are strategic aims that are oriented towards environmental management, social accountability and political excellence (Ozili, 2025). The following objectives drive organizations to invest in technologies such as AI that will assist in monitoring emissions and waste reduction as well as compliance. Companies that have well-defined sustainability pledges tend to use AI to pursue a more eco-friendly logistics operation, enhanced reporting precision, and competitive advantage in more environmentally conscious markets (Walter et al., 2025).

1.7 Organisation of the thesis

The thesis is divided into five major chapters as a way of giving a clear and logical flow of the research carried out on AI adoption, as far as sustainable supply chains in the Malaysian logistics industry are concerned.

Chapter 1: Introduction

The chapter explains the research topic, including the background and the context of AI application and sustainability in Malaysian logistics. It outlines the problem statement, the objectives of the research, research questions, the importance of the research, the scope and critical definitions. The thesis structure is also described in the chapter.

Chapter 2: Literature Review

The literature review will be reviewing other literature on the process of adoption of AI, sustainable supply chains, and logistics management, specifically in the context of Malaysia and other similar emerging markets. It explores the theoretical background addressing such frameworks as Technology-Organization- Environment and Diffusion of Innovation theory.

This chapter determines research gaps justifying the study.

Chapter 3: Research Methodology.

This chapter details the research methodology and design that was used to examine the readiness to adopt AI. It outlines the data collection procedures and the sampling techniques, the population, data collection instruments (e.g. survey or interviews) and the method of analysis. Ethical concerns and restrictions are also given.

Chapter 4: Finding and analysis.

Reporting of the research results in descriptive and inferential statistics, tables and graphs. The chapter comprehensively provides answers to the research questions by evaluating the relationships between complexity in supply chains, technological readiness, top management support, sustainable goals, and adoption of AI.

Chapter 5: Conclusion and Recommendations -

Concludes on the findings, theoretical and practical implications and provides future research and policy recommendations.

1.8 Summary

The first chapter is the central thesis of this thesis as it preconditions the discussion of the adoption of Artificial Intelligence (AI) in the field of sustainable supply chains in the Malaysian logistics Industry. It starts with the introduction of the topic of the research that notes the increasing role of sustainability and artificial intelligence integration in supply chain logistics in achieving both economic and environmental objectives. In the chapter, the author gives the background of the study, discussing the current trends in the industry, technological innovations, and the existing challenges of the Malaysian logistics companies to adopt AI technologies.

The Problem Statement explains the gap in the research, that the focus on AI readiness in the Malaysian logistics Industry has remained very small, even though this field is of paramount economic importance. It specifies the most important variables, such as AI adoption (dependent variable), sustainable supply chain (environmental variable), and supply chain complexity, technological readiness, top management support, and sustainable goals (independent variables) that put the study under investigation into perspective. Subsequently, the chapter describes the research questions and goals that will help the study to comprehend the determinants and the impact of AI adoption.

The Significance of the Study describes how this research benefits the academic theory by synthesizing various adoption frameworks as well as applied implications by providing practical implications to logistics companies, policymakers and technology suppliers. The scope also determines the limits of the research, that is, Malaysian logistics Industry in the period 2023-2025. The essential words are clarified so that the thesis does not have any confusion. The chapter ends on a note of thesis organization that gives the reader a roadmap of how the research is set out and how it will flow.

Overall, Chapter One provides the background, objective, and structure of the research which prepares the readers to an in-depth analysis of the AI adoption preparedness in sustainable supply chains of Malaysian logistics.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The logistics sector plays a critical role in the economic development of Malaysia, and the integration of Artificial Intelligence (AI) has been identified as a key factor in improving operational efficiency and sustainability. AI technologies, such as machine learning, predictive analytics, and automation, have shown great promise in enhancing logistics operations by optimizing demand forecasting, route planning, inventory management, and real-time decision-making (Culot, Podrecca, & Nassimbeni, 2024). The Malaysian logistics industry stands to benefit from AI's capabilities to streamline processes and address the challenges of increasing supply chain complexity and environmental sustainability goals (Rahim et al., 2024). However, despite the potential benefits, the adoption of AI remains relatively low within the sector, with companies facing several barriers that prevent them from fully integrating these technologies.

The AI readiness within Malaysia's logistics industry is still at an exploratory stage, with many companies recognizing the potential of AI but struggling with practical implementation. According to the AI Readiness Index Malaysia 2025, 84% of Malaysian companies are still in the early stages of AI exploration, especially in logistics, indicating that while the intent to adopt AI exists, actual deployment is limited (AI Malaysia, 2025). The barriers to full AI adoption in the logistics industry are diverse and multi-faceted, including challenges related to technological readiness, financial constraints, organizational culture, and policy limitations

2.1.1 The Role of Artificial Intelligence on Sustainable Supply Chains

AI increases supply chain visibility, prediction accuracy and operational efficiency hence cutting waste and carbon footprints. Inventory and routing are optimized by machine learning models to reduce the emissions and resource consumption, whereas analytics based on AI allow to reduce risks in advance and predict demand (Toorajipour et al., 2021). Pilot projects of AI-based logistic systems in Malaysia have shown a recent decrease of up to 20 percent in empty-mile trips and extreme enhancement of cold-chain services on perishable goods (Alam et al., 2025). AI can be used to develop circular supply chain practices, including reverse logistics and real-time rerouting, to synchronize logistics operations with Sustainable Development Goals (SDGs) by automating repetitive processes and supporting real-time decision-making.

2.1.2 Supply Chain Complexity on Artificial Intelligence

Complexities with the fragmented supplier base, multi-modal transport, and regulatory heterogeneity could both engender and retard AI uptake. Yet, in a more complex environment, the relative advantage for AI solutions in integrating disparate sources of data becomes sufficiently evident; one could also perceive that with complex legacy systems and interoperability issues, the implementation gets hindered (Rahim et al., 2024). Empirical studies denote a positive association between complexity and intention toward AI adoption, as moderated by organizations' integration capabilities (Lada et al., 2023).The proliferation of SMEs with nascent digital infrastructure in Malaysia further aggravates fragmentation, thus underscoring the importance of modular AI architecture that could embrace diverse data formats and partner capabilities.

2.1.*3* Technological Readiness on Artificial Intelligence

Technological readiness consists of infrastructure maturity, data quality, and digital skills. Uren and Edwards, (2023) frames process and data readiness, besides the ability to procure hardware, as necessary conditions for sustained successful AI. Organizations with well-defined IT architectures and data governance traverse AI deployment cycles at greater speeds and with higher systems reliability. In Malaysia, enterprises are still grappling with analytics capability and cloud adoption, which then places a hindrance on piloting AI into the big enterprises. However, with MyDIGITAL and the National AI Action Plan 2030, digital literacy is being enhanced, and cloud infrastructure costs are being subsidized, thereby raising the levels of readiness in the logistics industry (Yang et al., 2025).

2.1.4 Top Management Support on Artificial Intelligence

Top management willing to commit to something tends to allot resources and time strategically. It has been studied and documented that when senior managers maintain an innovation-oriented approach toward AI projects and personally involve themselves in project sponsorship, there tend to develop instances of organizational commitment and resistance to change diminishes (Chatterjee et al., 2024; Elrayah and Mirzaliev, 2024). Some Malaysian logistics companies state that adoption of AI-based decision support systems goes up by 30% if there is a C-level executive championing the digital transformation as compared to those Industry without such executive buy-in (Lada et al., 2023). The top-level commitment further sends signals on what organizations consider priorities and hence fosters cultures of experimentation and improvements.

2.1.5 Sustainable Goals on Artificial Intelligence

The AI investments that go beyond cost-saving endeavours are, in fact, backed by sustainability-oriented goals such as emission targets, resource efficiency, and corporate social responsibility. Load consolidation and modal shift optimization systems fit well under SDG 13 (Climate Action) and SDG 12 (Responsible Consumption and Production) (Yang et al., 2025). Pressure from the stakeholders and incentives from the Green Technology Master Plan on green logistics have made Malaysian logistics companies shift increasingly to sustainability-related reporting frameworks within AI parameters. Thus, explicit sustainability purposes provide vital momentum for AI towards improving environmental and social performance.

2.2 Underpinning Theory

2.2.1 Technology-Organization-Environment (TOE) Framework

Technology-Organization-Environment framework, which was initially created by Tornatzky and Fleischer, (1990), offers an extensive theoretical framework to trace the process of technology adoption in organizations by analysing three key dimensions of context Oliveira and Martins, (2011). The framework has shown a strong level of applicability regarding different technology adoption contexts and situations in organizational settings, which is why it is especially appropriate in researching the adoption of artificial intelligence in supply chain management.

The technological environment involves both the internal and external technologies that are applicable in the operations of an organization such as the existing technological capabilities, external technologies available, and the nature of innovation that are used in making decisions on adoption. In this background, the relative advantage, compatibility with the existing systems, complexity of implementation, and financial requirements are all influencing factors that determine the organizational perceptions and adoption decisions about artificial intelligence technologies Tornatzky and Fleischer, (1990).

Organizational context is the internal organization features such as size, structure, management support, resources available and cultural that affects capabilities of adopting technology and their adoption decisions. The literature shows that the organizational attributes play a massive role in success in the deployment of artificial intelligence by affecting the availability of resources, the implementation abilities and the effectiveness of change management Oliveira and Martins, (2011).

The environmental context is the external environment in which organizations are located such as industry features, competition, regulatory forces, and stakeholder demands that all have an impact on the decision-making regarding the technology adoption.

The environment presents both possibilities and barriers to the use of artificial intelligence as it defines organizational incentives and capabilities to implement the technology Tornatzky and Fleischer, (1990).

Technology-Organization-Environment framework gives theoretical insights into the interaction of technological, organizational, and environmental factors in the adoption of artificial intelligence in supply chain management. It is a recognition in the complex and multifaceted nature of technology adoption and offers structured analytical categories to study the process and outcome of the adoption.

2.2.2 Diffusion of Innovation DOI Theory

The theory of diffusion of Innovation as described by Everett Rogers describes how diffusion of innovations occurs in the social systems over time due to communication which are used to make decisions regarding adoptions Oliveira and Martins, (2011). This theory helps to learn important information about how technology adoption is time dependent and what are the aspects that determine when adoption is successful in various organizational setups.

The theory defines five major characteristics of innovation which affect adoption rates and success that are relative advantage, compatibility, complexity, trialability and observability. Relative advantage is the perceived advantage to innovation adoption in relation to that of current alternatives, and compatibility is the extent of compatibility between innovations and current values, experiences, and practices. Complexity is a perceived difficulty in apprehending and applying innovations, trialability is how the innovation can be experimented on small scale, and observability relates to the visibility of the advantages of the innovations to the potential adopters Oliveira and Martins, (2011).

The theory of Diffusion of Innovation focuses on the significance of channels of communication, systems, and time in determining the process of innovation adoption. The theory acknowledges that interpersonal communication, organizational networks, and social influence processes all affect the adoption decisions and serve as the factors that deter the formation of perceptions and attitudes towards innovations in general.

According to the theory, adopters are classified into five groups according to their innovativeness comprising: innovators, early adopters, early majority, late majority and laggards. Such classification assists in understanding why some organizations are early adopters of artificial intelligence technologies and others wait before adoption, which gives information on the temporal patterns of technology diffusion of services and organizational populations within industries.

2.2.3 Integration of Theoretical Framework

Technology-Organization-Environment framework and Diffusion of Innovation theory constitute a holistic theoretical framework that both covers the contextual factors and nature of innovation aspects that have an impact on the adoption of artificial intelligence in supply chain management. Although the Technology-Organization-Environment model provides an organizational level analysis that emphasize on contextual enablers and barriers, the Diffusion of Innovation theory offers an insight into the attributes of innovations and the process of their adoption that supplements the contextual analysis.

This theoretical synthesis is since the integration of artificial intelligence depends on a set of factors, which act in various mechanisms and on various levels of analysis. The organizational and environmental frames in Technology-

Organization Environment framework will add to the Innovation features and process of adoption highlighted in Diffusion of Innovation theory to form more comprehensive knowledge about adoption phenomena.

Studies that employ both theoretical frameworks prove to be stronger in explanation than the studies that employ a single theory in the case of technology adoption which is complex like the case of artificial intelligence adoption. This unified strategy offers sound theoretical modelling towards probing into the factors that determine the utilization of artificial intelligence in sustainable supply chain management and in recognition of the complexity of the organizational technology adoption practices Oliveira and Martins, (2011).

2.3 Hypothesis Formulation

The following hypotheses are proposed based on the reviewed literature.

2.3.1 Supply Chain Complexity Impact on Artificial Intelligence

H1: Growing supply chain complexity increases the intention to adopt AI in supply chain management

2.3.2 Technology Readiness Impact on Artificial Intelligence

H2: Greater technical readiness increases the intention to adopt AI in supply chain management.

2.3.3 Top Management Support Impact on Artificial Intelligence

H3: Stronger top management support increases the intention to adopt AI in supply chain management.

2.3.4 Sustainable Goals Impact on Artificial Intelligence

H4: Explicit sustainable goals increase the intention to adopt AI in supply chain management.

2.4 Research Framework

The development of the conceptual framework for this research was guided by two established theoretical frameworks: the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovation (DOI) theory. These frameworks were selected because they provide a comprehensive understanding of the factors influencing AI adoption in supply chain management, especially within the logistics industry. The

TOE framework allows for the examination of technological, organizational, and environmental factors, while the DOI theory addresses how innovations spread across organizations, considering adopter characteristics and attributes of the technology itself (Tornatzky & Fleischer, 1990; Rogers, 2003).

To adapt and adopt these frameworks to the specific context of AI adoption in the Malaysian logistics industry, I integrated four key determinants: supply chain complexity, technological readiness, top management support, and sustainability goals. These determinants were identified as the main influences on the readiness for AI adoption, based on both theoretical and empirical evidence from previous studies in technology adoption and logistics (Indravathy & Abd Rahim, 2024; Rahim et al., 2024).

The conceptual framework emphasizes the interaction of internal and external factors that influence AI adoption. The internal factors include organizational readiness and management support, which are critical for overcoming resistance to change and facilitating the integration of AI systems. The external factors, such as supply chain complexity and sustainability goals, help organizations determine the urgency and potential benefits of adopting AI to meet operational and environmental challenges (Baker, 2011).

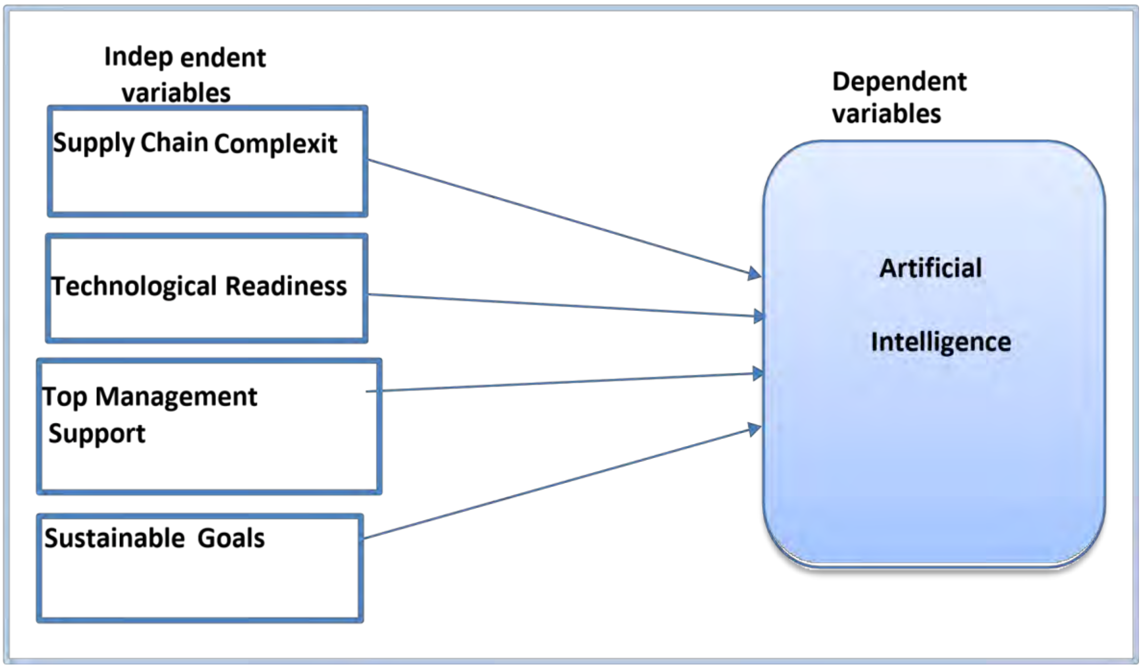

Figure 2. 1 Research Framework

2.5 Summary

AI adoption in Malaysia's logistics sector has the potential to revolutionize operations, improve efficiency, and contribute to sustainability goals. However, significant barriers remain, including challenges related to technological readiness, high implementation costs, and organizational resistance. Government policies aimed at supporting digital transformation are valuable, but further interventions are needed, particularly to support SMEs and enhance executive buy-in. The literature review highlights that while AI adoption holds significant promise for the Malaysian logistics industry, overcoming these barriers requires coordinated efforts from both industry players and policymakers. Future research should focus on understanding the long-term impacts of AI adoption and explore the organizational and cultural factors that influence successful integration.

One of the major barriers to AI adoption in Malaysian logistics is the lack of technological readiness. Many logistics companies are still operating on legacy systems that are not compatible with modern AI tools, making it difficult to integrate these technologies into existing infrastructure (Indravathy & Abd Rahim, 2024). The digital infrastructure required to support AI solutions, including cloud computing, data storage systems, and real-time data analytics platforms, is often underdeveloped or non-existent in many firms, particularly in small and medium-sized enterprises (SMEs) (Uren & Edwards, 2023). Moreover, the quality of data required for AI algorithms to function efficiently is often inadequate, as many logistics companies still rely on manual data entry and disconnected databases, leading to inefficiencies in AI system performance (Alam et al., 2025).

In addition to technological limitations, cost concerns are another significant barrier to AI adoption. AI technologies require substantial upfront investment, not only in purchasing software and hardware but also in training employees to operate and maintain these systems. For SMEs, this financial burden can be prohibitive, especially given that the benefits of AI, such as cost savings and efficiency improvements, may take time to materialize (Rahim et al., 2024). Despite government initiatives offering financial support for digital transformation, such as the National AI Roadmap and the Malaysia Digital Economy Blueprint (2021-2030), the adoption of AI remains limited among smaller firms due to the high costs associated with implementation (Mida, 2025).

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter explains the research design that was applied to explore the readiness to adopt Artificial Intelligence (AI) in the context of sustainable supply chains in the Malaysian logistics. Adoption of AI has become one of the major components to enhance efficiency, sustainability, and competitiveness within the logistics industry particularly supply chain management. The chapter aims to discuss the research framework, research design, study area and population, sample technique, and sample size, data collection strategies through which a detailed picture on the research methodology of the study will be presented.

3.2 Research Design

This study has a quantitative research design as it seeks to establish how various factors affect the adoption of Artificial Intelligence (AI) in sustainable supply chains. Quantitative approach enables gathering of numerical data so that patterns are set and no hypothesis regarding relationships between variables are tested (Creswell, 2009). This type of research design is especially appropriate to examining the breadth and nature of AI adoption because it offers an objective, measurable means of evaluating the impacts of supply chain complexity, technological readiness, top management support, and sustainable goals on AI adoption (Creswell, 2009). Through surveys, the study can gather substantial data in a sample that is representative of the overall population and hence the generalizability of the result (Sekaran and Bougie, 2016).

Also, by doing this, you can test out specific hypotheses, which gives you a systematic method to verify or disprove theoretical relationships among the variables involved.

3.3 Study area and Population

The total population for this study consists of 272 registered logistics companies that are members of the Association of Malaysian Hauliers (AMH). These companies, involved in various logistics and transportation services across Malaysia, represent the target population for this research. The study focuses on managerial-level employees within these companies, specifically those in roles such as Assistant Managers, Supervisors, and Middle/Senior Managers, who are directly involved in decision-making related to AI adoption and digital transformation within their organizations.

The sample size for this research was determined to be 211 respondents. This sample size was calculated based on the total population of 272 logistics companies and is deemed statistically sufficient to provide reliable and valid results for the study. A 95% confidence level and a 5% margin of error were used in the sample size calculation, ensuring a high level of certainty in the research findings.

To select the sample, the study employed purposive sampling, targeting individuals who are best positioned to provide valuable insights into the factors influencing AI adoption in their organizations. These respondents were drawn specifically from the AMH membership database, ensuring that the companies included are actively involved in logistics operations and are likely to have experience with AI adoption. By using purposive sampling, the research ensures that the sample consists of individuals who are directly engaged in the processes of evaluating and integrating AI technologies into logistics operations.

3.4 Sampling Technique and Sample Size

The sampling method in this study is the purposive sampling method that best suits the study as it is aimed at targeting people who are most knowledgeable and relevant to the focus of this study which is the use of AI in the sustainable supply chain within the Malaysian logistics industry (Fowler, 2013). This will help the researcher to identify participants who are directly engaged in logistics processes, and they might be exposed or have experience with AI technologies. The sample will be derived in the Association of Malaysian Hauliers (AMH) and other players in the logistics and transportation industry. Through purposive sampling, the research will also be confident that it will only include those organizations and individuals who are most likely to give valuable information on the topic of adoption of AI leading to more focussed and meaningful data.

In terms of sample size, the research is expected to involve 211 respondents, namely, managers, associate managers, and supervisors of the organizations that belong to these logistics. Such individuals are chosen since they are usually in charge of routine activities and decision-making in their respective departments and, therefore, are well placed to give pertinent information as to the factors that influence the adoption of AI. This is a representative sample size as it is big enough to provide a wide scope of views and at the same time, it enables the management of data that is easy to handle and reflective of different levels in an organization in the logistics Industry. Through these roles, the research could acquire a detailed data of the impact of organizational preparedness, technological preparedness, and the leadership support on the adoption of AI in supply chain management.

3.5 Questionnaire Design

To investigate the role of artificial intelligence Adoption (AI Adoption) in sustainable supply chains in Malaysian logistics industry, this study created a structured questionnaire as the primary tool for data collection. The questionnaire was carefully designed based on a comprehensive review of previous literature and relevant theoretical foundations in supply chain management, sustainability, and technology application. Each construct used in this study was operationalized into measurable items, reflecting conceptual clarity and contextual relevance for companies in Malaysia.

Measurement items were used from instruments validated in preceding studies, with minor modifications to make the items appropriate to the local context and easier for survey respondents to understand. All items are measured on a six-point Likert scale from 1= (strongly disagree) to 6 = (strongly agree) as this decreases central tendency bias and can produce differentially extreme responses (Koo and Yang, 2025). The survey is divided into five core sections regarding independent variables (supply chain complexity, technology readiness, top management support, and sustainability goals) as well as demographic questions so the researchers may gain context about the typology of respondents and make future analyses more robust.

Table 3. 1**:** Constructs and Sources

No	Variables	Items	Scale	Source
1	Artificial Intelligence Adoption	**AI1:** Our organisation applies AI in supply chain processes such as forecasting, planning, and logistics. **AI2:** AI-generated insights are regularly used to improve supply chain decision-making. **A13:** Our AI systems are integrated with our existing supply chain operations. **A14:** The use of AI in our supply chain has increased in recent years. **A15:** Our organisation is committed to expanding AI adoption in the supply chain in the future.	Likert Scale	(Cannas et al., 2024)
2	Supply Chain Complexity	**SCC1:** Our supply chain involves a wide network of partners that work together effectively. **SCC2:** We manage a diverse range of products and processes successfully within our supply chain. **SCC3:** The interconnections across our supply chain functions contribute to stronger collaboration. **SCC4:** Our organisation responds effectively to changes in demand and supply conditions. **SCC5:** We manage extensive data and information flows in a structured and efficient manner.	Likert Scale	(Aelker et al., 2013)

3	Technological Readiness	**TR1:** Our IT infrastructure is well developed to support AI applications in supply chain activities. **TR2:** Our organisation has reliable and accessible data for effective use in AI solutions. **TR3:** Employees in our organisation are capable of using digital and AI-enabled tools. **TR4:** We use integrated platforms that connect data across different supply chain functions. **TR5:** Our organisation is well prepared to expand AI applications across the supply chain.	Likert Scale	(Ali & Khan, 2025) (Felemban et al., 2024)
4	Top Management Support	**TMS1:** Senior management consistently communicates the importance of adopting AI in our supply chain. **TMS2:** Top management provides sufficient resources and budget for AI-related initiatives. **TMS3:** Leaders actively encourage collaboration among departments to implement AI. **TMS4:** Senior management establishes clear responsibilities for AI projects in the supply chain. **TMS5:** Our management recognises and supports teams that successfully implement AI solutions.	Likert Scale	(Al-Husseini, 2024)
5	Sustainable Goals	**SG1:** Our organisation has established clear and measurable sustainability targets for supply chain operations. **SG2:** Environmental and social considerations are integrated into our supply chain decisions.	Likert Scale	(Caiado et al., 2018)

		SG3: We regularly monitor sustainability indicators to improve supply chain performance. **SG4:** Our sourcing and logistics practices are aligned with sustainability principles. **SG5:** Sustainability objectives play an important role in our investment decisions for supply chain technologies.		

3.6 Instrument and Scale

The instrument used in this study was a structured questionnaire designed to measure the factors influencing the adoption of Artificial Intelligence (AI) in the Malaysian logistics industry. The questionnaire was developed based on an extensive review of prior studies on AI adoption, supply chain management, and technology acceptance, ensuring that all measurement items were theoretically grounded and aligned with the objectives of the study. Established and validated measurement scales from previous empirical research were adapted to fit the context of the Malaysian logistics sector, with minor modifications to ensure clarity and relevance.

To ensure content validity, the initial version of the questionnaire was reviewed by academic experts in the fields of logistics management, supply chain systems, and information technology. The experts evaluated the relevance, clarity, and adequacy of each item in representing the intended constructs. Based on their feedback, several items were reworded to improve clarity and to ensure that the instrument accurately captured the constructs under investigation.

3.6.1 Variables of the Instrument

The questionnaire measures five main variables derived from the Technology–Organization–Environment (TOE) framework and the Diffusion of Innovation (DOI) theory, which form the theoretical foundation of this study. These variables are supplying chain complexity, technological readiness, top management support, sustainability goals, and AI adoption.

Supply chain complexity refers to the degree of operational complexity faced by logistics companies, including the number of supply chain partners, diversity of products, coordination challenges, and uncertainty in demand and delivery processes. This variable captures how increasing complexity may influence the need for advanced technologies such as AI to improve coordination and decision-making (Aelker, Bauernhansl, & Ehm, 2013).

Technological readiness reflects the extent to which logistics firms possess the necessary digital infrastructure, data quality, and technical capabilities required for AI implementation. This includes the availability of information systems, data integration capabilities, and employees' technical skills. Previous studies have shown that organizations with higher technological readiness are more likely to adopt AI successfully (Uren & Edwards, 2023).

Top management support measures the level of commitment, involvement, and resource allocation provided by senior management toward AI adoption. This variable assesses whether top management actively promotes AI initiatives, supports organizational change, and provides strategic direction, all of which are critical for successful technology adoption (Al-Dubai & Alaghbari, 2018).

Sustainability goals refer to the extent to which environmental and social sustainability considerations influence organizational decisions. This variable examines whether logistics firms view AI as a tool to improve energy efficiency, reduce emissions, minimize waste, and enhance overall sustainable supply chain performance (Caiado et al., 2018).

AI adoption, the dependent variable, measures the extent to which AI technologies have been implemented in logistics operations. This includes the use of AI for demand forecasting, route optimization, inventory management, decision support, and process automation. The items assess both the current level of AI usage and the organization's intention to expand AI implementation in the future (Cannas et al., 2024).

3.7 Data Collection Strategy

The research data will be collected via an online survey, which will offer an effective and convenient method of acquiring data of a geographically spread sample. Due to the logistics companies that are targeted in Malaysia, the online format will ensure that many respondents within the Association of Malaysian Hauliers (AMH) and other stakeholders in the logistics industry are reached. This approach is best suited to the managers, associate managers and supervisors because these professionals are directly engaged in the decision making and operations hence, they are well placed to give information on the implementation of AI technologies in their organizations.

The survey will target 211 participants, specifically the ones in the managerial and supervisory positions since they are the primary decision-makers when it comes to the adoption of AI in supply chain management. This is the right sample size as it will help the study to collect a wide variety of opinions, which will give credible data to analyse.

The survey will be carried out in a span of four weeks to ensure that the survey is carried out in time, and the respondents can fill out the survey at their own convenience. In addition to this, to improve the level of participation, non-respondents will be reminded frequently during the data collection period. Anonymity and confidentiality of the survey will be highlighted to ensure that the respondents provide honest and unbiased answers to the survey questions to make sure that the information gathered is accurate and complete. This will enable the research to obtain useful information about the drivers of AI adoption in the Malaysian logistics industry.

3.8 Data Analysis Technique

This research information was gathered using an online questionnaire which was administered using Google Forms where several respondents could be efficiently and widely reached through the instrument, which includes managers, associate managers, and supervisors in the logistics industry. Online survey administration is widely recognised as an effective data collection method for reaching geographically dispersed respondents and enhancing response efficiency and representativeness in organizational research (Sekaran and Bougie, 2016; Saunders, Lewis, and Thornhill, 2019). The online method allowed the study to access an extremely geographically spread sample, thereby increasing the representativeness of the data for the population of interest.

After the data was collected through the survey, statistical analysis was performed using SPSS, a widely used and reliable statistical software for analysing quantitative data in social science and management research (Pallant, 2020; Field, 2024). SPSS is particularly suitable for handling large datasets and conducting both descriptive and inferential statistical analyses in behavioural and organizational studies.

Descriptive statistics were used as the starting point of the analysis process to provide a clear overview of respondents' characteristics and their perceptions regarding the adoption of artificial intelligence (AI). Descriptive analysis enables researchers to summarise central tendencies and variability in the data, thereby offering an initial understanding of trends and patterns among the study variables (Hair et al., 2019). This step is essential for

addressing Research Question 1 (RQ1) as it facilitates the generalisation of overall patterns related to technological readiness, supply chain complexity, top management support, sustainability goals, and AI adoption within the Malaysian logistics industry.

Following the descriptive analysis, correlation analysis was conducted to examine the relationships among the key variables and to address Research Question 2 (RQ2). Pearson's correlation coefficient was employed to measure the strength and direction of linear relationships between the independent variables supply chain complexity, technological readiness, top management support, and sustainable goals and the dependent variable AI adoption. Pearson correlation is widely applied in management and logistics research to assess the degree of association between continuous variables prior to hypothesis testing (Field, 2024; Hair et al., 2019).

Finally, multiple regression analysis was applied to test the research hypotheses and to address Research Question 3 (RQ3). Regression analysis assists in determining the extent to which each independent variable contributes to explaining variations in the dependent variable while controlling for the effects of other predictors (Creswell, 2014; Hair et al., 2019). Through this method, the study was able to identify the most significant factors influencing AI adoption in the Malaysian logistics industry, including supply chain complexity, technological readiness, top management support, and sustainable goals.

Overall, the combination of descriptive statistics, correlation analysis, and regression analysis provides a robust analytical framework for examining organizational readiness and identifying key enablers and barriers to AI implementation in sustainable supply chains (Pallant, 2020; Saunders et al., 2019).

3.9 Chapter Summary

The paper presents the research design that the researcher used to investigate the variables that affect the use of AI in sustainable supply chains in the Malaysian logistics Industry. The study takes a quantitative research design, involving the use of structured online questionnaire, which will be administered via Google Forms, to collect data form the managers, associate managers, and supervisors in the logistics industry. The study sample was 210 respondents, who were chosen through a purposive sampling method to include those who were directly engaged in the decision-making processes about the adoption of AI.

The data obtained was examined in SPSS (Statistical Package of the Social Sciences). The analysis was conducted in three phases descriptive analysis, correlation analysis and regression analysis. The descriptive analysis gave a summary of the characteristics and trends of the sample regarding the field of AI adoption and addressed Research Question 1 (RQ1). Correlation analysis was conducted on the relationship between the key variables such as supply chain complexity, technological preparedness, top management support, and sustainable goals which aided in answering the Research Question 2 (RQ2). Lastly, regression analysis confirmed the research hypotheses and addressed Research Question 3 (RQ3) and gave information on the strength and significance of the associations between the independent variables and AI adoption.

These ways help the chapter successfully describe the systematic way of comprehending the factors that led to the adoption of AI in the logistics Industry. The results of the analysis are predicted to bring beneficial information to the scholarly work and hands-on practice in the sphere of sustainable supply chain management.

CHAPTER FOUR

RESULT AND DISCUSSION

4.0 Introduction

In this chapter, the results of the analytics are given in six parts. To begin with, the demographic profile describes the major features of participants to put the dataset into perspective. Second, descriptive analysis summarises all constructs central tendency and dispersion. Third, reliability analysis is used to review internal consistency of the measurement scales (e.g., Cronbach's alpha). Fourth, Pearson displays bivariate relationships in terms of direction, strength and significance. Fifth, multiple linear regression evaluates the profile effects of predictors on the result variable, model fit, and diagnostics. Lastly, a hypothesis summary briefly describes the decision made with each hypothesis at the pre-decided level of significance.

4.1 Demographic Profile

The next part is about the people who were in this study. The respondents' backgrounds include their age, gender, level of education, type of company, position level, and years of experience.

From table 4.1, most of the people in the sample are young and just starting their careers. Of the 211 people who answered, 88 (41.71%) are under 25, 91 (43.12%) are between 25 and 35, and 84.83% are under 35. Only 26 people (12.32%) are between the ages of 35 and 45, and only 6 people (2.85%) are over the age of 45. The sample has 112 females (53.10%) and 99 males (46.90%), which is almost equal. This supports an interpretation of the results that encompasses both genders. A lot of the people in this group have a lot of education. 103 (48.80%) have a bachelor's degree, 62 (29.30%) have a Diploma, 40 (18.96%) have a master's degree, and 6 (2.85%) have a PhD. This shows that they are highly qualified and that there are a lot of people with advanced degrees. There are 112 jobs (53.10%) in businesses that are owned by people in the area or by the government, 53 jobs (25.10%) in businesses that are owned by the government, and 46 jobs (21.80%) in businesses that are based in other countries. This means that the results mostly show what happens in the private Industry at home, but they also show some public and international points of view. Most managers are at the senior level 101 (47.80%), then at the middle level (51 or 24.20%), then at the supervisory level 46 (21.80%), and finally at the associate level 13 (6.20%). This means that the answers come from people who have a lot of power to make decisions. Based on the age structure, work experience shows that this person is in the early to middle of their career (n=211 valid responses for this item). There are 88 people (41.70%) who say they have less than 5 years of experience, and 91 people (43.10%) who say they have more than 5 years of experience. 84.80% of people have been together for 5 to 10 years, 12.80% for 10 to 15 years, and 2.40% for more than 15 years. To find the percentages of valid responses for each variable in SPSS, you should use different bases for experience. Most of the people in the sample are women who are well-educated, work for local private companies, have a lot of management experience, and have been working for less than ten years. This is something you should keep in mind when you look at the study's attitudes, practices, and results for the organisation.

Table 4. 1: Age

Category	**Frequency**	**Percent**
< 25 Years	88	41.71
> 45 Years	6	2.85
25 Years - 35 Years	91	43.12

35 Years - 45 Years	26	12.32
Total	211	100

Table 4.1 shows the age distribution of the respondents. It indicates that most respondents are in the 25-35 years age group (43.12%), followed by the under 25 years group (41.71%). The remaining respondents are more evenly distributed between the 35-45 years (12.32%) and over 45 years (2.85%) age groups. This age distribution suggests that most respondents are relatively young and likely to be in the early to middle stages of their careers. This is an important demographic, as younger professionals are generally more open to adopting new technologies like AI, which could influence the results of the study on AI adoption in the logistics sector.

Table 4. 2: Gender

Category	Frequency	Percent
Female	112	53.1
Male	99	46.9
Total	211	100

Table 4.2 provides the **g**ender distribution of the respondents, showing that the majority of respondents are female (53.1%), while 46.9% are male. This gender balance is quite significant, as it provides a more diverse perspective on the adoption of AI, which is often a male-dominated field, particularly in industries like logistics. The representation of both genders in this study allows for more inclusive insights into how AI adoption might differ across gender lines in the logistics sector, especially in terms of leadership support, organizational culture, and the adoption process

Table 4. 3: Educational Level

Category	Frequency	Percent
Bachelor's degree	103	48.8
Diploma	62	29.3
Master's degree	40	18.96
PhD	6	2.85
Total	211	100

Table 4.3 shows the educational level of the respondents. The majority hold a bachelor's degree (48.8%), followed by Diploma holders (29.3%), and master's degree holders (18.96%). A small percentage (2.85%) have completed PhDs. This indicates that most of the respondents are well-educated and possess a solid academic background, which is crucial when analysing their technological readiness and their ability to understand and implement AI technologies in logistics operations. The high educational qualifications of the respondents suggest that they are likely to be open to new ideas and technologies, and their perspectives on AI adoption are likely to be informed by their knowledge and experience.

Table 4. 4: Type of Company

Category	Frequency	Percent
International	46	21.8
Local / Government-owned	53	25.1
Local / Private-owned	112	53.1
Total	211	100

Table 4.4 provides information on the type of company the respondents are working for. The majority of respondents are from local, private-owned companies (53.1%),

followed by government-owned companies (25.1%) and international companies (21.8%). This distribution reflects the structure of the Malaysian logistics industry, where private sector companies dominate the landscape. This table suggests that the study captures a significant portion of the local private sector perspective on AI adoption. The company type could influence how AI adoption is perceived and implemented, as private companies might face different challenges and opportunities compared to government-owned or international firms, particularly in terms of resource allocation, innovation culture, and governmental policy influenc.

Table 4. 5: Position Level

Category	Frequency	Percent
Associate-level Manager	13	6.2
Middle-level Manager	51	24.2
Senior-level Manager	101	47.8
Supervisory Level	46	21.8
Total	211	100

Table 4.5 presents the position level of the respondents. The largest group is from senior-level management (47.8%), followed by middle-level managers (24.2%), supervisory level (21.8%), and assistant-level managers (6.2%). This distribution is significant because senior-level managers are typically responsible for making strategic decisions about AI adoption, whereas middle managers and supervisors are often involved in the operational implementation of these technologies. The inclusion of respondents from all levels of management ensures that the study captures a holistic view of AI adoption, from strategic planning to day-to-day execution, providing a comprehensive understanding of the organizational factors that influence AI adoption in logistics.

Table 4. 6: Years of Experience

Category	Frequency	Percent
< 5 years	88	41.7
> 15 years	5	2.4
10 - 15 years	27	12.8
5 - 10 years	91	43.1
Total	216	100

Table 4.6 shows the years of experience of the respondents. The largest group has between 5 to 10 years of experience (43.1%), followed by those with less than 5 years (41.7%), 10 to 15 years (12.8%), and more than 15 years (2.4%). This suggests that the respondents are primarily mid-career professionals, with a good amount of industry experience but still in the process of advancing in their careers. This experience is particularly valuable when assessing their readiness for AI adoption, as individuals with moderate to extensive experience may have a clear understanding of both current challenges and technological opportunities in the logistics industry.

4.2 Descriptive Analysis

The descriptive analysis for RO1 reveals that while logistics Industries in Malaysia exhibit relatively high levels of readiness and strategic intent towards AI adoption, the actual adoption of AI by the logistics Industry was noted to be moderate. The findings then emphasize the need to operationalize technologies such as technology capacity, organizational leadership, and commitment to sustainability, to capitalize fully on the benefits of a digital transformation in the logistics industry.

Table 4. 7: Descriptive Analysis

Variables	N	Minimum	Maximum	Mean	Std.Deviation
Supply chain complexity	211	1.4	6	4.2995	0.82494
Technological readiness	211	1.6	6	4.5299	0.8329
Top_management_support	211	1.6	6	4.3573	0.85628
Sustainable goals	211	2.8	6	4.6256	0.7406
Ai adoption	211	1.6	6	4.1299	0.81627

Table 4.7 provides the descriptive statistics for the key variables: Supply Chain Complexity, Technological Readiness, Top Management Support, Sustainable Goals, and AI Adoption. The table shows the mean, standard deviation, minimum, and maximum values for each variable. For example, Technological Readiness has a mean of 4.53 (SD = 0.83), indicating that most respondents perceive their companies as having a relatively high level of digital infrastructure and data capabilities. Similarly, Sustainability Goals scored high, with a mean of 4.63 (SD = 0.74), reflecting that many logistics companies are aligning their operations with sustainability objectives. On the other hand, AI Adoption has a mean of 4.13 (SD = 0.82), suggesting that while AI adoption is moderate, there is still room for improvement in fully integrating AI into logistics operations. The standard deviations indicate that there is some variation

in responses, which reflects the heterogeneity of experiences and perspectives within the sample.

4.3 Reliability Analysis

Using Cronbach's alpha, a reliability analysis was performed on five multi-item scales (five items per scale). Internal consistency was observed to be good to very good across constructs: supply chain complexity ($\alpha = 0.851$), technological readiness ($\alpha = 0.783$), top management support ($\alpha = 0.852$), sustainable goals ($\alpha = 0.830$), and AI adoption ($\alpha = 0.785$). All coefficient scores exceed the acceptable benchmark of .70, and most exceed .80, supporting the "good" reliability, as considered by classical guidelines to psychometric testing, as well as contemporary approaches to multivariate analysis of variance (Hair et al., 2019). In the spirit of best practice, future validity work could do well to provide composite reliability (CR $\geq$ .70) and average variance explained (AVE $\geq$ .50), as part of fit appraisals, and thereby pair internal consistency (alpha) with evidence of convergent validity and construct reliability (Hair et al., 2019).

The pattern of coefficients is also consistent with previous research on these constructs. For example, technological readiness scales, including the Technology Readiness Index family of scales, consistently report acceptable-to-good alphas because the items appropriately capture coherence between infrastructure, data, and skills (Parasuraman & Colby, 2015). Top management support often returns high reliability as it captures an organization's leadership commitment, resource allocation, and legitimizing organizational change (Al-Dubai & Alaghbari, 2018). verifiably solid intention of supports for sustainable goals when looking at strategic emphasis on environmental and social (Kuckertz and Wagner, 2010). For the category of AI adoption, intention use constructs based on models of have repeatedly demonstrated robust reliability across multiple contexts in organizations (Venkatesh et al., 2003). Finally, a strong alpha for supply chain complexity is consistent with operations-related scholarship, treating it as latent multi-dimensional phenomenon and operationalized with scale bas and checked reliability and validity before testing structure (Pant et al., 2025).

Table 4. 8: Reliability Analysis

Variables	No of Items	Cronbach's Alpha
Supply chain complexity	5	0.851
Technological readiness	5	0.783
Top management support	5	0.852
Sustainable goals	5	0.830
Ai adoption	5	0.785

4.4 Pearson Correlation

Correlation is a measurement of the strength of linear association between two variables. There are three potential ways that these two variables may correlate: a positive linear correlation, a negative linear correlation, or no correlation at all (Field, 2024). The correlation coefficient known as Pearson's correlation coefficient will be used to examine the relationship between the variables in the study (independent and dependent variables).

Pearson's product-moment correlation coefficient (r) calculates the strength and direction of the linear association that may exist between two continuous (or approximately interval-scaled) variables, with values ranging between -1 (perfect negative) through 0 (no linear association) to +1 (perfect positive). Statistical significance is typically assessed through a two-tailed p-value with underlying assumptions of linearity, bivariate normality, and no influential outliers. Movement away from these assumptions may distort r and the associated test (Cohen, 1988). The findings of the Pearson correlation for RO2 indicate that Industries with higher adoption rates for AI have higher technological readiness and managerial capability, and also have a stronger alignment with sustainability goals, showing that digital transformation through AI is a key enabler of long-term competitive and environmental performance in the Malaysian logistics industry.

4.4.1 There is a significant correlation between Supply chain complexity and AI adoption.

The positive correlation identified between supply-chain complexity and AI adoption ($r = .583$) corresponds with the information-processing theory of operations: as interdependence, variability, and uncertainty increase, the marginal value of analytics/AI in providing visibility, forecasting, and coordination increases too, and the business case for adoption is strengthened. Foundational work on complexity drivers frames complexity as a latent, multi-dimensional condition that raises information needs (Pant et al., 2025). Current literature reviews, and empirical studies show that, at higher complexity, analytics AI capabilities are more positively associated with resilience and performance implying that within more complicated contexts, higher complexity will convert readiness and manager support into actualized deployments (Laguir et al., 2023).

Table 4. 9: There is a significant correlation between Supply chain complexity and AI adoption

Variable	**Supply chain complexity**	**Ai adoption**
Supply chain complexity	1	----------
Ai adoption	.583**	1

**. Correlation is significant at the 0.01 level (2-tailed).

4.4.2 There is a significant correlation between Technological Readiness and AI adoption.

Table 4.9 show the relationship between technological readiness and AI use is positive (r = .592), suggesting that organizations with better digital infrastructure, higher quality data, and skills that complement AI are significantly more likely to implement AI solutions. This relationship aligns with the Technology–Organization–Environment (TOE) perspective, which argues that tech-related capabilities lower adoption risk and increase perceptions of usefulness (Baker, 2011), as well as the accumulating IS/IT evidence that technological capabilities and perceived usefulness influence acceptance use(Venkatesh et al., 2003). From an empirical perspective, TOE-based organizational studies report that strong IT capability and data readiness leads to greater adoption intensity, controlling for other factors (Abulail et al., 2025).

Table 4. 10: There is a significant correlation between Technological Readiness and AI adoption

Variable	**Technological Readiness**	**Ai adoption**
Technological Readiness	1	--------------
Ai adoption	0.592**	1

**. Correlation is significant at the 0.01 level (2-tailed).

4.4.3 There is a significant correlation between Top Management Support and AI adoption.

Table 4.10 show the positive association of TMS and AI adoption (r = .450) suggests that when executive sponsorship with its attendant budget, priorities, and legitimation is strong, it is accompanied by higher levels of AI uptake. Top management, in both the organizational change and IS adoption literature helps alleviate uncertainty and overcome resistance from middle management, taking organizations from technical readiness to actual use (Al-Dubai & Alaghbari, 2018). In acceptance models, leadership support operates through perceived usefulness and facilitating conditions, raising intention and subsequent behaviour (Venkatesh et al., 2003). All in all, the association noted fits in line with the governance channel highlighted by TOE (Baker, 2011) when top management endorses and budgets for AI initiatives, AI adoption will take place.

Table 4. 11: There is a significant correlation between Top Management Support and AI adoption.

Variable	Top Management Support	Ai adoption
Top Management Support	1	-------------
Ai adoption	0.450**	1

**. Correlation is significant at the 0.01 level (2-tailed).

4.4.4 There is a significant correlation between Sustainable Goals and AI adoption.

Table 4.11 show the positive relationship between sustainability goals and AI adoption (r = .515) indicates that organizations with SG agendas are more likely to engage with AI to support optimization, monitoring, and disclosure. Reviews of data-driven supply chains have pointed out that sustainability objectives can "pull" analytics AI into the operational domain more routinely (Ozili, 2025), and the broader sustainability literature highlights the potential for digital-led capabilities to facilitate low-carbon distributed coordination and transparency (Sarkis, 2020). In practice, organizations inclined more heavily towards SG agendas demonstrate a tendency toward using AI to monitor emissions and resource efficiency and support reporting a series of mechanisms that are aligned with the coefficient observed and apparent in supply-chain analytics frameworks that link capability with sustainability performance (Ozili, 2025).

Table 4. 12: There is a significant correlation between Sustainable Goals and AI adoption.

Variable	Sustainable Goals	Ai adoption
Sustainable Goals	1	---------------
Ai adoption	0.515**	1

**. Correlation is significant at the 0.01 level (2-tailed).

4.4.5 Discussion

Table 4.12 show the correlation matrix suggests that AI adoption is positively and significantly related to all four of the important predictors: technological readiness ($r = .592$, $p < .01$), supply chain complexity ($r = .583$, $p < .01$), sustainability objectives ($r = .515$, $p < .01$), and top management support ($r = .450$, $p < .01$). These coefficients indicate that AI adoption is associated with moderate to high effect sizes (Cohen, 1988), which implies that although the technology is not broadly implemented in Industry, organizations with advanced technology, involved in complex networks and with sustainability objectives are likely to adopt AI into their logistics processes. Technological readiness is the strongest correlate which suggests that the combination of access to digital infrastructure, skilled workforce and data quality, leads to AI adoption into logistics. Conversely, while top management support remains significant, it plays an essential, but more of a supportive role, as the acceptance and resource allocation for technological change is legitimized.

The results confirm the Technology–Organization–Environment (TOE) framework proposed by Baker in 2011, reiterating that technological capability, organizational leadership, and environmental pressures combine to drive digital innovation. The strong relationship between technological readiness and AI utilization consistent with the work of Venkatesh et al.'s (2003) and Abulail et al.'s (2025) research. They suggested that the capability of technology heightens perceived usefulness and reduces resistance to the development and adoption of new systems. Similarly, the notable relationship between top management support and AI utilization parallels the findings of Al-Dubai and Alaghbari's (2018) work where management and sponsorship is crucial to the successful implementation of technology.

The positive relationship between sustainability goals and AI use aligns with Sarkis' 2020; Ozili’s 2025) findings that AI could support environmental stewardship using enhanced data analytics, carbon tracking, and logistics routing to support full supply chain efforts. The significant relationship between supply chain complexity and AI is also aligned with the antecedents' findings (Laguir et al., 2023; Seif & Jafari, 2025) that show Industry that are subject to higher levels of uncertainty and interdependence are also likely to utilize AI for predictive analyses, automation, and resilience-building. Taken together, these findings suggest that the mechanism of AI technology does not solely improve operational efficiencies but also assists in developing sustainable and adaptive supply chain systems.

Notwithstanding the strong correlations observed, some limitations have to be recognized. To begin with, the cross-sectional nature of the study prevents the establishment of causal connections – it cannot be determined which one influenced the other, AI adoption or sustainability results. Moreover, the use of self-reported data might lead to the introduction of a subjective bias, since the respondents might claim their technological readiness or sustainability practices to be higher than they really are. Besides, the research work takes into account only the Malaysian logistics companies and this may be a constraint in generalizing the study findings to other Industries or geographical areas. Plus, there could be unknown factors like regulations, company size, or availability of funds that could either directly or indirectly impact the relationships between the constructs and thus affect the correlations that are caught by the study. The dynamic AI adoption process and its effects on sustainability in the long run should be drawn through a longitudinal method of research in the future. Quantitative surveys and qualitative interviews could be designed to provide practical insights into the challenges of AI implementation. Besides, the research could be expanded to cross-national comparative studies within ASEAN to spot the differences in digital transformation and sustainability performance due to the context. Not only that, but also the use of structural equation modelling (SEM) to include mediating and moderating variables such as organizational learning, innovation culture, and government incentives would be instrumental in providing a broader comprehension of AI's role in the development of sustainable supply chains.

4.5 Multiple Linear Regression

The regression analysis under the assumption of RO3 draws attention to the fact that technology readiness continues to top other enablers for implementing AI, whereas sustainability objectives, supply chain complexities, and top-management support simultaneously enhance technology readiness for logistics Industry. These observations emphasize efforts to invest in technology innovation to improve AI supply chain readiness in Malaysia’s logistics Industry.

In this section, there will be a thorough analysis of the results obtained using Pearson’s correlation between independent variables supply chain complexity, technology readiness, top management support, sustainability goals and dependent variables AI adoption. The analysis will relate to understanding the practical and theoretical implications of both the strength and direction of these results not only within these defined parameters but also to the limits to which inferences to these results are permissible.

Table 4. 13: Multiple Linear Regression

	Coefficients			**95% Confidence Interval**	
Variables	**B**	**Std. Error**	**Sig**	**Lower Bound**	**Upper Bound**
(Constant)	-0.392	0.296	0.187	-0.975	0.191
Supply chain complexity	0.23	0.06	0.001	0.113	0.348
Technological readiness	0.379	0.051	0.001	0.278	0.481
Top management support	0.136	0.05	0.008	0.037	0.235
Sustainable goals	0.264	0.062	0.001	0.141	0.388

a. Dependent Variable: Artificial Intelligence Adoption.

R^2 = .552, Adjusted R^2 = .544, p<0.001

4.5.1 Discussion

Table 4.13 show the multiple linear regression (MLR) assesses the independent (partial) contribution of each predictor toward estimating a continuous outcome while controlling for each other. Unstandardized coefficients (B) represent the amount of change expected in the dependent variable for a one-unit change in the predictor, the 95% CI represents uncertainty in estimation, the p-value tests H_0: B = 0, and

R^2/Adjusted R^2 represent total explained variance (Hair et al., 2019). When offering interpretations of magnitudes, the theory of context should be supplemented for generic guidelines on effect size (Cohen, 1988).

The regression model for AI adoption was statistically significant, $R^2 = .552$ and Adjusted $R^2 = .544$ ($p < .001$) and this indicated that the four predictors explained approximately 55% of the variance in adoption together. All four predictors demonstrated a positive and statistically significant coefficient (two-tailed tests): technological readiness (B = 0.379, SE = 0.051, 95% CI [0.278, 0.481], P-value = .001), sustainable goals orientation (B = 0.264, SE = 0.062, 95% CI [0.141, 0.388], P-value = .001), supply chain complexity (B = 0.230, SE = 0.060, 95% CI [0.113, 0.348], P-value = .001), and top-management support (B = 0.136, SE = 0.050, 95% CI [0.037, 0.235], P- value = .008). The constant was not statistically significant (B = −0.392, p = .187). Substantively, technological readiness increased one-unit was associated with AI adoption increasing by 0.379, when controlling for the remaining predictors; similar interpretations can be made for sustainability (0.264), complexity (0.230), and TMS (0.136). These are all partial effects that reveal individual contributions to the predictive validity that are above the other predictors or drivers.

4.6 Hypothesis Summary

H1: Supply-chain complexity to AI adoption.

The table 4.14 shows the positive and statistically significant coefficient suggests that Industry with higher complexity in their supply chains are adopting AI higher than lower complexity Industry, holding other things equal. From an information-processing standpoint, the greater the interdependence, the greater the variability, and the greater the uncertainty, increases the value of analytics and AI to better visibility, forecasting, coordination and for ever increasing payoffs to adoption (Ahmed et al., 2024). Recent review articles of supply chains follow suit and link analytics capability under higher complexity sustainability, performance, and success, which elucidates why pressures of complexity coincide with higher volumes of AI uptake (Lada et al., 2023).

H2: Technological readiness to AI adoption.

The greatest coefficient among the predictors indicates that having strong infrastructure, high data accuracy, interoperability, and complementary capabilities will lead to significantly higher adoption, while controlling for the other drivers. This supports the Technology-Organization-Environment (TOE) perspective, which regards the technological capability construct as a proximal antecedent which mitigates the risk of adoption and enhances perceived usefulness (Baker, 2011). Empirical studies can't yet definitively establish the claims, but generally ecology of studies supports that greater technology readiness predicts greater assimilation consistent with acceptance mechanisms (perceived usefulness, facilitating conditions). Synthesis on AI in supply chains same story: capability is a first-order driver of AI deployment (Culot et al., 2024).

H3: Top-management support to AI adoption.

While the effect is smaller in size than readiness, it nevertheless has a positive significant effect, which suggests that executive sponsorship offers theoretically incremental explanatory power on top of technology and contextual characteristics. Executive sponsorship accords legitimacy to initiatives, opens new budget channels to evaluate existing priorities, binds the organization to relevant objectives, and introduces some reduction in actionably uncertain channels, all of which have consistently been shown to improve adoption intention and related use(Al-Dubai & Alaghbari, 2018). Regarding acceptance, top-management sponsorship improves facilitating conditions and perceived usefulness as they relate to readiness or intention to use, and therefore help convert readiness to use (Venkatesh et al., 2003).

H4: Sustainability goals to AI adoption.

This positive, important coefficient indicates that sustainability goals that are more enhanced pull AI into operations for optimization, monitoring, and disclosure (e.g., emissions tracking, efficiency of resource use, audit trails). The data-driven supply chain literature outlines this ESG-led demand for analytic AIs (Chatterjee et al., 2024), as do the more general sustainability literatures that note how digital capabilities form the foundation for transparency and low carbon coordination (Sarkis, 2020).

Table 4. 14: Hypothesis Summary

Hypothesis test	Coefficients	Sign	Decision
H1	0.23	0.001	Supported
H2	0.379	0.001	Supported
H3	0.136	0.008	Supported
H4	0.264	0.001	Supported

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Discussion and Conclusion

This paper discussed the impact of the complexity of supply chains, technological readiness, the support of the top management and sustainability objectives on the implementation of AI in the Malaysian logistics Industry. The results show that the degree of preparedness toward the adoption of AI is moderate to high particularly concerning the availability of technological capabilities, leadership participation and sustainability projects, but the level of actual adoption of AI is lower than projected, which indicates a gap between awareness and actual implementation. The complexity of the supply chain became one of the key factors in the adoption of AI since companies with dynamic, globalized and data-intensive supply chains need intelligent technologies to improve visibility and decrease uncertainty. This finding is consistent with Pant et al., (2025). who have determined that as the complexity of operations rises, advanced analytics and AI are increasingly used to enhance coordination of networks in supply chains, and with Laguir et al., (2023). who have stated that digitalization is an urgent necessity when supply chains increase in scale and uncertainty.

The strongest impact was identified to be caused by technological readiness among the independent variables, which shows that companies that possess stronger digital infrastructure and data quality, as well as skilful IT personnel will be in a better position to alter AI initiatives into the stage of active implementation instead of merely planning. Likewise, findings by Baker, 2011;Venkatesh et al., (2003) confirmed that one of the main requirements of AI adoption in logistics transformation is technological capability. The importance of the top management support was also confirmed within the frames of this research, which proves the fact that the top management is essential in terms of the resource's distribution, establishment of innovation-friendly conditions, and overcoming the change resistance. This observation industry Venkatesh et al., (2003), who established that the role of leadership in Industry 4.0 adoption is substantial and aligned with the background TOE framework developed by Tornatzky and Fleischer (1990), which identifies leadership commitment as an organizational driver enabler of technological change.

Additionally, the findings proved that the sustainability objectives contribute greatly to the adoption of AI, especially to boost fuel efficiency, decreasing carbon emissions, and raising resource optimization. This is in line with Ozili, (2025) who pointed out that environmental performance pressures increase the chances of adopting smart and sustainable logistics technologies, and Sarkis, (2020) who pointed out that sustainability initiatives build the incentive to use AI to enhance the environmental and supply chain performance of Industry. Although these factors are positive, the level of AI use is still low in the logistics companies of Malaysia; this fact aligns with Ozili, (2025);Sarkis,(2020) who also identified the lack of workforce capability and the problems of system integration as among the challenges of AI implementation in the developing economies. Overall, the study gives good empirical evidence of the Theory of Technology-Organization-Environment (TOE) and Diffusion of Innovation (DOI) both theories show that successful AI adoption is determined by internal preparedness and perceived value of innovation. To this end, this paper concludes that the Malaysian logistics companies are shifting towards AI-enabled sustainability, but they need to invest more in the technological advancement, human resources, and organizational dedication before turning the willingness into the successful and transformative application.

5.2 Implication of the Study

5.2.1 Theoretical Implication

This assessment contributes to the advancement of theoretical knowledge on AI adoption since it connects sustainability objectives to TOE and DOI models. The findings indicate that environmental motivations are a key determinant of digitalisation of logistics systems. Another contribution made by the study is the integrated view of the interaction between internal (technology and leadership) and external (complexity and sustainability pressure) operational problems to form the innovation adoption behavior. The results empirically suggest the use of TOE and DOI in logistics in the emerging economies.

5.2.2 Practical Implication

5.2.2.1 Implications for Organizations

The results indicate that technological readiness is a strong marker of adoption of AI which implies that logistics companies need to keep developing strong digital infrastructure and enhance data integration in the scope of the supply chain operations. As the companies invest in more advanced systems like cloud solutions, automated tracking systems, and solutions based on data-driven analytics, they will be more visible and responsive in their logistics operations. This is since such investments make the AI systems capable of functioning efficiently and providing valuable insights to make forecasts, maximize inventory, and optimize routes. Also, robust IT competence can assist businesses to overcome integration issues that usually make AI remain in the plan stage and not translate into full operation application.

Another vital ingredient that is eminent in this study is organizational change management. AI adoption may not be effective despite the presence of technology because employees can be resistant or may not easily abandon old systems. Hence, the top management should be highly supportive to foster the innovation culture, deploy the required resources, and develop clear strategic guidelines on using AI. The engagement of leadership is associated with the minimization of fear and uncertainty, the promotion of cross-departments cooperation, and the motivation of employees to perceive how AI must contribute to long-term organizational objectives. Training and skill development are to be provided continuously as well because the employees would need to be able to use AI-enabled tools and make informed decisions based on real-time information.

The findings also validate that sustainability objectives are influential in promoting the use of AI and this shows that companies should incorporate environmental and social objectives in technology plans. With AI monitoring emissions, waste, and energy use, organizations can become more efficient in their operations, as well as increase their sustainability performance. This alignment would also be able to increase competitive advantage with customers, regulators, and partners in the global supply chain calling more and more on transparent and responsible logistics operations. Sustainability should not be viewed as an independent goal to fully capitalize on this value but integrated into the digital decision-making process.

Lastly, organizations must reinforce data management and system security to defend sensitive logistics data in the process of adopting AI solutions. It is also important to ensure that various supply chain systems work together so that partial connectivity of the systems leads to poor data visibility and less accuracy in AI. Effective cybersecurity and standardized data operations allow the management to have increased confidence in the digital transformation, which makes it easier to incorporate AI technologies. All these organizational activities trust in transforming preparedness into success adoption and durable operation advantages.

5.2.2.2 Implications for Policy Makers

The implications of the present study suggest a serious necessity of policymakers to strengthen digital transformation in the Malaysian logistics industry. Since the level of technological readiness has a significant effect on the implementation of AI, national government agencies should help businesses to create the necessary digital infrastructure and sophisticated data management systems that will facilitate sustainable operations. These involve enhancing broadband coverage in industrial areas, strengthening data-sharing policies, and backing the standards of cybersecurity that safeguard sensitive supply chain data. Enhancing these functions will make the transition of the logistics Industry out of the traditional systems into the AI-enabled decision-making in operational processes more successful and effective.

In addition, the results indicate that sustainability objectives play an important role in the adoption of AI. Thus, the policies of the country must incorporate sustainability incentives in the development of logistics. Funding programs led by the government, tax breaks or grants on AI projects in relation to emission reduction, route optimization, or minimization of wastes would speed up the adoption of green technology in the logistics industry. Moreover, the identification of companies that have obtained sustainability milestones with the help of AI might encourage others to do the same. It is important to align the adoption strategies with the national development plans like the Malaysia Digital Economy Blueprint and the National AI Roadmap to ensure that the logistics Industry has played its part in making the nation competitive, resilient and sustainable in terms of the environment, and long-term innovation of the economy.

It is also important to develop human capital that can perform AI. The government ought to increase specialized upskilling, professional qualifications, and industry-academia affiliations on the application of AI in logistics operations. Such programs will contribute to solving the problem of skills deficit and allow the employees to work with digital systems. Funding to the SMEs with budget constraints will also mean that the adoption of technology is not highly concentrated in the big corporations. Together, these policies can help a policymaker create a better external ecosystem that will help attract logistics companies to use AI regularly, consistently, and in a sustainable way.

5.3 Limitations of the Study

While the current study has merit for the assessment of AI for adoption in the logistics Industry in Malaysia, it does come with limitations that should be noted. First, it was conducted through the use of a cross-sectional research design, as it required data to be collected at a particular point in time. As a result, it would not be able to report on how perspectives of readiness and adoption change as organizations move through their process of digital transformation. The adoption of AI is not a discrete decision but a process that transpires with changing conditions based on the relative development of technology, market pressures and sustainability planning. Since trends and adoption will always consider multiple variables, the findings are only accurate about current perspectives and do not represent potential organizational behavior over the longer term. Future studies could employ longitudinal studies and eventually capture the activities from early readiness of adoption to levels of maturity.

Second, the limited context of the study that centered only on logistics companies in Malaysia. However, despite logistics being an important contributor to th economy and sub-Industry with sustainability challenges, it reduced the findings' applicability. Other industries may experience different technology approaches or expectations for sustainability and how this might impact AI uptake. Differences in the business environment, policies, and infrastructure of Malaysia relative to other countries illustrate that caution should be taken in applying this research beyond the logistics context in Malaysia. Cross-industry and cross-country comparisons could enhance those recommendations.

5.4 Recommendation

Given the limitations and findings from this research, several recommendations for future research directions were outlined. First, this research utilized a cross-sectional design, measuring adoption readiness only at a single point in time. Future research should consider using a longitudinal study, which would be a more reliable way to gauge adoption progress or how sustainability performance changes over the course of the technology's maturation period. Even after the readiness factors have influenced the adoption decision, AI assimilation takes time, so tracing the organizations over time would allow for a more thorough understanding of the factors in readiness influencing AI adoption outcomes, over time.

Second, while this study examined the logistics Industry in Malaysia, future research should consider expanding the scope by examining multiple Industries across regional economies. By conducting a comparison of logistics Industry and organizations within the manufacturing, retail, or service-based industries, researchers may help comprehend regional factors of performance, which impact adoption readiness factors.

Likewise, comparing readiness research across the ASEAN region or other developing countries will assist practice and policy makers understand best performance practices, benchmark the industry performance and encourage regional cooperation associated to developing sustainable supply chains, which also encompasses AI readiness and governance.

Additionally, future research should examine other variables that improve the predictive ability of AI use models: organizational culture, financial readiness, supply chain partnerships, or regulatory pressures. Their use of interviews, case studies, or ethnographic observation allows researchers to examine behavioural, managerial and operational areas that were not directly observable and/or documented through self-reported quantitative surveys. This will yield a richer contextual environment and allow for more strategic recommendations to influence internal rationales toward AI adoption and expedite implementation and use of the technology.

In the end, this recommendation will work toward contributing a more inclusive body of knowledge that better addresses theoretical contributions and has a more practical relevance for decision-making to understand the role of AI in changing sustainable logistics.

5.5 Conclusion

In conclusion, this study successfully demonstrated that technological readiness, top management support, supply chain complexity, and sustainability goals are all significant predictors of AI adoption in the Malaysian logistics industry. The findings align with the theoretical frameworks of Technology-Organization-Environment (TOE) and Diffusion of Innovation (DOI), which emphasize the interplay between organizational, technological, and environmental factors in driving technology adoption. The positive correlations found between these factors and AI adoption confirm that companies with better technological capabilities, strong leadership support, more complex supply chains, and a focus on sustainability are more likely to adopt AI technologies.

The study also highlights the importance of policies and initiatives aimed at improving technological infrastructure, leadership commitment, and support for SMEs in the logistics sector. As AI continues to play a crucial role in shaping the future of the logistics industry, fostering a conducive environment for AI adoption is essential to enhancing operational efficiency and sustainability in the sector. Future research should explore longitudinal studies to track the impact of AI adoption on performance outcomes in the logistics industry and expand the scope to include other emerging technologies.

This research contributes valuable insights into the AI adoption process within the logistics sector, providing actionable recommendations for policymakers, industry leaders, and organizations seeking to improve their digital transformation strategies. As Malaysia continues to move toward Industry 4.0, this study's findings offer a roadmap for addressing the challenges and leveraging the opportunities that AI presents to the logistics sector.

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APPENDICES QUESTIONNAIRES

Dear Respondents,

I'm Mustafa Abdiaziz Ahmed. a student of Master of Science (Transportation and Logistics Management) from the School of Technology Management & Logistics (STML), University Utara Malaysia. You are invited to participate in an academic research study that aims to assess the **readiness of the Malaysian logistics industry to adopt Artificial Intelligence (AI)** for achieving a **sustainable supply chain**. The study explores key factors such as technological readiness, Top Management Support supply chain complexity, and sustainability goals in enhancing AI adoption readiness.

Your participation is **voluntary**, and all information provided will be **kept strictly confidential** and used **only for academic purposes**. There are **no right or wrong answers**—please answer each question honestly based on your experience or perception.

The questionnaire will take approximately **7–10 minutes** to complete.

If you have any questions about the research, you may contact the researcher at: +601164018209 or ahmedassigments@gmail.com

Thank you very much for your valuable time and contribution to this study. Your insights are essential to understanding how the logistics industry in Malaysia can move toward a smarter and more sustainable future.

Sincerely,

Mustafa Abdiaziz Ahmed

School of Technology Management & Logistics (STML)

University Utara Malaysia

Instructions:

Please respond to each statement with whatever knowledge you have by circling your answer using the scales given. There is no right or wrong answer. Be honest in your assessment.

Section A: Demographic Information

Thank you for participating in this research. Please (√) answer the following questions honestly and to the best of your knowledge.

1. Gender

A) Male

B) Female

2. Age of the respondents

A. <25 ☐

B. 25-35 ☐

C. 35-45 ☐

D. 35-40 ☐

E. >45 ☐

3. Level of education

A. Diploma

B. Bachelor Degree

C. Post-Graduate Level (master's or PhD)

4. Position Level

A. Senior Level

B. Associate Level

C. Supervisory Level

5.Type of Company

A. International

B. Local/Private-owned

C. Local Goverement-owned

D. Other

6. Years of Experiance

A. <5 years

B. 5-10 years

C. 10–15 years

D. >15 years

Section B: Supply Chain Complexity

Scale	**Description**
1	Strongly disagree
2	Disagree
3	Slightly disagree
4	Slightly Agree
5	agree
6	Strong agree

No	**Supply Chain Complexity**	**SD**	**D**	**SD**	**SA**	**A**	**SA**
1	Our supply chain involves a wide network of partners that work together effectively.						
2	We manage a diverse range of products and processes successfully within our supply chain.						
3	The interconnections across our supply chain functions contribute to stronger collaboration.						
4	Our organisation responds effectively to changes in demand and supply conditions.						

5	We manage extensive data and information flows in a structured and efficient manner.						

No	Technological Readiness	SD	D	SD	SA	A	SA
1	Our IT infrastructure is well developed to support AI applications in supply chain activities.						
2	Our organisation has reliable and accessible data for effective use in AI solutions.						
3	Employees in our organisation are capable of using digital and AI-enabled tools.						
4	We use integrated platforms that connect data across different supply chain functions.						
5	Our organisation is well prepared to expand AI applications across the supply chain.						

No	Top Management Support	SD	D	SD	SA	A	SA
1	Senior management consistently communicates the importance of adopting AI in our supply chain.						
2	Top management provides sufficient resources and budget for AI-related initiatives.						
3	Leaders actively encourage collaboration among departments to implement AI.						

4	Senior management establishes clear responsibilities for AI projects in the supply chain.						
5	Our management recognises and supports teams that successfully implement AI solutions.						

No	**Sustainable Goals**	**SD**	**D**	**SD**	**SA**	**A**	**SA**
1	Our organisation has established clear and measurable sustainability targets for supply chain operations.						
2	Environmental and social considerations are integrated into our supply chain decisions.						
3	We regularly monitor sustainability indicators to improve supply chain performance.						
4	Our sourcing and logistics practices are aligned with sustainability principles.						
5	Sustainability objectives play an important role in our investment decisions for supply chain technologies.						

Section C: Artificial Intelligent Adoption

Please respond to each statement with whatever knowledge you have by **TICK** your answer using the scales given. SD = Strongly Disagree, D = Disagree, SD= Slightly Disagree, SA = Slightly Agree, A = Agree, and SA= Strong Agree

No	Artificial Intelligent Adoption	SD	D	SD	SA	A	SA
1	Our organisation applies AI in supply chain processes such as forecasting, planning, and logistics.						
2	AI-generated insights are regularly used to improve supply chain decision-making.						
3	Our AI systems are integrated with our existing supply chain operations.						
4	The use of AI in our supply chain has increased in recent years.						
5	Our organisation is committed to expanding AI adoption in the supply chain in the future.						

END OF SURVEY

THANK YOU VERY MUCH FOR YOUR KIND COOPERATION