ANALYZING THE FACTORS THAT AFFECTS THE ARTIFICIAL INTELLIGENCE ADOPTION IN SUPPLY CHAIN

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APPROVAL

I, Nurul Izzati Binti Asmadi, hereby declare that the research conducted in this study titled "Analyzing the Factors that Affects the Artificial Intelligence Adoption in Supply Chain" is my original work. Any sources used have been properly acknowledged and referenced. The research has been undertaken to fulfil the requirements of Bachelor of Technology Management (Supply Chain and Logistic) at Universiti Teknikal Malaysia Melaka.

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This report is submitted in fulfilment of the requirement for the Bachelor of Technology Management (Supply Chain Management and Logistic)

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DECLARATION

I declare that this report is my original work. Any summaries or quotations included are properly referenced, and their sources have been clearly mentioned. I take full responsibility for the content of this report, ensuring it represents my personal effort and research.

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ABSTRACT

The adoption of artificial intelligence (AI) in the supply chain industry has transformational potential, with increased efficiency, accuracy, and creativity. This study attempts to examine the most important factor impacting AI adoption in the supply chain industry. Descriptive statistics and multiple regression models were used to uncover important factor of AI adoption. This report gave a comprehensive understanding of the essential factor that influence AI adoption in the supply chain sector. The findings provided useful insights for practitioners and policymakers working to promote AI integration, highlighting the need of improving technology capabilities, fostering supportive organizational cultures, and dealing with external constraints. Practical guidelines had been presented to help organizations navigate their AI adoption path, guaranteeing a deliberate approach to using AI for supply chain excellence. The expected results shows that technological readiness, defined as the availability of modern IT infrastructure and experienced individuals, is the most important factor driving AI adoption. Organizational support, such as top management commitment and an innovative culture, is also important. Additionally, external forces like as competitive dynamics and the regulatory environment have a substantial impact on AI adoption decisions.

ABSTRAK

Penggunaan kecerdasan buatan (AI) dalam industri rantaian bekalan mempunyai potensi transformasi, dengan peningkatan kecekapan, ketepatan dan kreativiti. Kajian ini cuba mengkaji faktor terpenting yang memberi kesan kepada penggunaan AI dalam industri rantaian bekalan. Statistik deskriptif dan model regresi berbilang digunakan untuk mendedahkan faktor penting penggunaan AI. Laporan ini memberikan pemahaman menyeluruh tentang faktor penting yang mempengaruhi penggunaan AI dalam sektor rantaian bekalan. Penemuan ini memberikan pandangan berguna untuk pengamal dan penggubal dasar yang berusaha mempromosikan integrasi AI, menonjolkan keperluan untuk meningkatkan keupayaan teknologi, memupuk budaya organisasi yang menyokong dan menangani kekangan luaran. Garis panduan praktikal telah dibentangkan untuk membantu organisasi menavigasi laluan penggunaan AI mereka, menjamin pendekatan yang disengajakan untuk menggunakan AI untuk kecemerlangan rantaian bekalan. Hasil yang dijangkakan menunjukkan bahawa kesediaan teknologi, yang ditakrifkan sebagai ketersediaan infrastruktur IT moden dan individu yang berpengalaman, adalah faktor paling penting yang mendorong penggunaan AI. Sokongan organisasi, seperti komitmen pengurusan atasan dan budaya inovatif, juga penting. Selain itu, kuasa luar seperti dinamik persaingan dan persekitaran kawal selia mempunyai kesan yang besar terhadap keputusan penggunaan AI.

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CHAPTER 1

INTRODUCTION

1.0 Introduction

The supply chain industry has both significant opportunities and problems as a result of the quickly developing artificial intelligence (AI) technologies, which are revolutionising decision-making and operations management. AI presents challenges including implementation hurdles, talent shortages, and ethical issues, but it also presents chances to improve productivity, optimise workflows, and facilitate data-driven insights. This study looks at important factors that affect supply chains' adoption of AI, with a particular emphasis on differences in AI integration and how it affects operational effectiveness. Uneven AI adoption frequently leads to a fragmented supply chain environment, where some businesses benefit from cutting-edge technology while others face challenges due to inadequate infrastructure and resource constraints.

A thorough grasp of the organisational, technological, and environmental elements that either support or impede the adoption of AI is one of the anticipated results of this study. By determining these elements, the research hopes to clarify the main forces behind and obstacles that businesses encounter when using supply chain models powered by artificial intelligence. Because it provides practical insights for supply chain experts, legislators, and business executives, this study is important. Stakeholders can promote innovation, enhance decision-making procedures, and bolster competitiveness in a changing market environment by tackling the obstacles and using AI's potential. The ultimate goal of this study is to open the door for an ecosystem of supply chains powered by AI developments that are more robust, sustainable, and efficient.

1.1 Background of The Study

In today's rapidly changing business sector, the adoption of Artificial Intelligence (AI) technology into supply chain management is becoming more common. AI has tremendous potential for optimising operations, improving decision-making processes, and streamlining many aspects of supply chain activity. However, despite its potential benefits, AI adoption in the supply chain sector continues to differ in terms of implementation and effectiveness across businesses.

Understanding the elements that influence AI adoption in supply chain management is critical for organisations looking to take full advantage of its changing possibilities. Such insight may help with strategic decision-making, resource allocation, and execution methods, eventually leading to increased competitiveness and operational efficiency. Improving procedures and operations in the logistics and supply chain requires artificial intelligence. According to Toorajipour, Sohrabpour, and Fisch (2021), artificial intelligence (AI) is a broad field of computer learning that focuses on creating intelligent machines that are capable of carrying out tasks that would typically need human intellect. A number of studies have shown the benefits of incorporating artificial intelligence (AI) into supply chain and logistics, including decreased risks and expenses, enhanced operational effectiveness, and better customer service (Toorajipour, Sohrabpour & Fischl, 2021; Modgil, Singh & Hannibal, 2021).

Savoury (2019) reports that supply chain management firms are utilising artificial intelligence (AI) for network monitoring, virtual assistants, and CRM systems. However, there are issues because many of these applications are still conceptual and have not produced a profit. The purpose of this study is to investigate the various dynamics surrounding the adoption of AI in supply chain management. A thorough knowledge may be achieved by examining the elements that impact the adoption process, such as technological, organisational, and environmental aspects. Examining the obstacles and possibilities connected with AI adoption in supply chain management can also give useful insights for practitioners, policymakers, and researchers.

This study aims to contribute to the body of knowledge on AI adoption in supply chain management by conducting strong clear research and theoretical analysis.

By identifying major adoption factors, hurdles, and facilitators, it attempts to give practical suggestions for organisations to effectively manage the challenges of incorporating AI technology into their supply chain processes.

According to Telefonica (2023), the use of artificial intelligence (AI) offers a practical method for allocating resources appropriately in response to the variety of activities that occur on a daily basis. Finally, the study's conclusions seek to enable informed decision-making and promote the effective adoption and deployment of AI-driven solutions in supply chain management.

1.2 Problem Statement

The supply chain sector must embrace artificial intelligence (AI) if it is to increase operational effectiveness, enhance decision-making, and gain a competitive edge. Even with the obvious advantages, incorporating AI technology remains a substantial hurdle for many supply chain organisations. To facilitate a more seamless transition and optimise the possible advantages of artificial intelligence (AI) in supply chain operations, it is essential to recognise and comprehend these elements.

Technological impediments that hinder the successful use of AI include inadequate IT infrastructure and a shortage of trained workers. Advanced technology integration is a common source of frustration for organisations, which results in inefficiencies and subpar performance. Furthermore, many supply chain entities find it challenging to close the knowledge gap caused by the quick speed at which AI is developing. It is imperative to tackle these technological obstacles in order to create an atmosphere that is favourable to the adoption of AI.

The adoption of AI is also significantly influenced by organisational variables. Implementing AI projects can be hampered by lack of strategic vision, managerial resistance, and resistance to change. Moreover, outside forces like competitive dynamics and regulatory limitations affect an organization's capacity to successfully implement AI technology. The purpose of this study is to methodically examine these variables in order to offer a thorough grasp of the obstacles and facilitators to the adoption of AI in the supply chain sector. The knowledge acquired will help develop solutions for these problems, which will eventually lead to a wider and more efficient application of AI in supply chains.

1.3 Research Objectives

1. Identify the factors that affects the artificial intelligence adoption in supply chain.
2. Analyze the most significant factor that affects the artificial intelligence adoption in supply chain.

1.4 Research Questions

1. What factors that affects the artificial intelligence adoption in supply chain?
2. What is the most significant factor that affects the artificial intelligence adoption in supply chain?

1.5 Expected Outcomes

This study will conduct a thorough analysis to identify and categorise the crucial factors impacting the adoption of Artificial Intelligence (AI) in supply chain management. These considerations might include technology readiness, organisational culture, leadership support, resource availability, regulatory restraints, and market dynamics.

By studying technical aspects, the research seeks to give insights into organisations' readiness to implement AI technology in their supply chain processes.

This involves assessing the maturity of AI solutions, their compatibility with current systems, and the availability of experienced workers for AI deployment and maintenance.

This study aims to give insight on the organisational dynamics that influence AI adoption in supply chains. This includes organisational culture, leadership vision, decision-making procedures, and the allocation of resources to AI initiatives. Understanding these processes is essential for developing successful methods to overcome organisational hurdles to AI adoption.

Other factors such as legal frameworks, industry standards, and market conditions have a substantial impact on AI adoption in supply chain management. The study's goal is to examine the impact of these external forces and make suggestions to help organisations negotiate compliance obstacles and capitalise on market possibilities.

The study is intended to reveal sectoral and organisational differences in the adoption and application of AI technologies across the supply chain. By comparing and contrasting adoption patterns across sectors and organisational sizes, the study will shed light on the motivations and challenges unique to each setting.

Based on the findings, the research intends to make strategic suggestions for organisations looking to incorporate AI technology into their supply chain operations. These recommendations will provide actionable insights to overcome technological, organisational, and external issues, supporting the effective adoption and deployment of AI-driven solutions in supply chain management.

1.6 Significance of the Study

The importance of researching the variables influencing the adoption of Artificial Intelligence (AI) in the supply chain arises from its ability to give significant insights and direction to organisations navigating the challenges of digital transformation. This finding has numerous important consequences.

Understanding the factors that influence AI adoption in the supply chain allows organisations to make more informed decisions about technology investments, resource allocation, and organisational restructuring. Identifying crucial aspects and their influence allows organisations to build focused strategies to expedite AI adoption and achieve a competitive advantage in the market.

The effective use of AI technology has the potential to simplify supply chain processes, increase efficiency, and lower costs. Organisations may improve overall operational performance by analysing the variables that impede or assist AI deployment.

In today's fast-paced corporate climate, implementing AI in the supply chain can give a substantial competitive edge. Organisations that successfully embrace AI technology may adapt faster to market changes, satisfy consumer requests more efficiently, and reinvent their supply chain operations to remain ahead of competition. Understanding the variables that influence AI adoption is critical for organisations looking to capitalise on these competitive advantages.

AI adoption provides potential for innovation and growth in the supply chain ecosystem. Organisations that embrace evolving technology can explore new business models, develop creative solutions, and provide value-added services to clients. Analysing the elements that influence AI adoption can help organisations overcome innovation barriers and promote a culture of continuous development and growth.

Adoption of artificial intelligence in the supply chain is not without dangers, such as technological obstacles, data security problems, and regulatory compliance issues. Organisations that recognise possible risks and problems connected with AI adoption can establish comprehensive risk management systems to reduce threats and protect their operations. This research can assist organisations in proactively managing risks and building resilience in their supply chain systems.

Finally, this study contributes to the body of information regarding AI adoption in the supply chain area. This study promotes understanding in the subject by synthesising current research, producing new insights, and making practical recommendations. It also serves as a platform for future research and academic inquiry.

1.7 Summary

In summary, this study has shed light on the many enablers and hurdles that affect the supply chain industry's adoption of artificial intelligence. AI integration is greatly impacted by organisational reluctance, outside influences, and technological obstacles including poor IT infrastructure and a lack of qualified workers. The study offers a thorough insight that may direct resource allocation and strategic decision-making by methodically looking at these variables. In the end, these observations hope to make the adoption of AI easier while also improving the supply chain industry's competitiveness and operational effectiveness.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

The adoption of Artificial Intelligence (AI) technology in supply chain management marks an important point in the growth of modern business processes. As organisations increasingly recognise AI's potential to transform traditional supply chain operations, recognising the numerous variables affecting its adoption has become critical. This literature study examines existing research and scholarly debate on the variables influencing AI adoption in the supply chain sector.

AI adoption in supply chain management has the potential to increase efficiency, optimise operations, and enable data-driven decision-making at all levels of the supply chain. From demand forecasting and inventory optimisation to logistics and distribution, AI-powered solutions have disruptive capabilities that may have a substantial influence on organisational performance and competitiveness. AI-improved instruments are being used throughout supply chains to improve effectiveness, decrease the influence of a global staff shortage and find improved solutions to move supplies from one spot to another location. Customer care focus vendors are using AI to understand their key population to improve planning about their future behaviour (Sagiroglu & Sinanc, 2013).

In summary, understanding the variables that influence AI adoption in the supply chain is crucial for organisations looking to effectively employ AI technology to improve operational efficiency and achieve a competitive advantage. This literature review synthesises current research and gives a complete overview of the important variables that drive or impede the adoption of AI in the supply chain sector, establishing the framework for empirical research and evaluation in the next parts of this study.

2.1 Definition of Terms

2.1.1 Artificial Intelligence (AI)

Artificial intelligence (AI) is the development of computer systems that can do activities that normally require human intelligence. These activities include comprehending normal language, identifying patterns, learning from experience, and making judgements. AI includes a wide range of techniques, such as machine learning, natural language processing, computer vision, robotics, and expert systems. Artificial intelligence is revolutionising several industries, including supply chain and logistics (Kersten, Blecker, & Ringle, 2019). Artificial intelligence does not relate to any specific technology. According to Sharma, Sharma, and Jindal (2021), the term accurately describes several technical techniques.

AI systems have a wide range of applications, including healthcare, finance, transportation, manufacturing, and customer service. They have the ability to automate repetitive jobs, optimise processes, enhance decision-making, and provide previously unachievable capabilities and services. Overall, AI is an innovative technology with the ability to alter businesses, increase productivity, and improve people's lives. However, it creates ethical, societal, and economic concerns that must be carefully considered in order to assure responsible development and deployment. AI technology is now widely used in applications including navigation, face recognition, and spam filtering (Tai, 2020).

The big data age has led to increased use of data mining and deep learning technologies in supply chains. Growing data sets pose challenges for organisations in terms of storage and processing. Constantiou and Kallinikos (2015) argue that maintaining and using data is crucial for improving brand strategy and sales. AI can assess large amounts of data, understand relationships, prioritise activities, and improve policy formation. According to Davenport et al. (2020), artificial intelligence might be a matchmaker

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2.1.1.1 Type of Artificial Intelligence (AI) in Supply Chain

Artificial intelligence (AI) is a broad term that includes several subfields and kinds, each with unique uses and features. Three primary categories may be used to categorise AI which is Narrow AI, General AI, and Superintelligent AI. These classifications are based on capabilities. Weak AI, often referred to as narrow AI, describes AI systems like voice assistants like Alexa and Siri, recommendation engines, and picture recognition software that are intended to perform a limited number of tasks. Strong AI, often known as general AI, refers to AI systems that are capable of carrying out any intellectual work that a person can. General AI, however, is still theoretical and has not yet been implemented. Artificial intelligence (AI) that is more intelligent than humans and capable of handling any intellectual activity is referred to as superintelligent AI.

Theory of Mind, Limited Memory, Reactive Machines, and Self-aware AI are the four main categories of AI based on functionality. Basic artificial intelligence systems known as "Reactive Machines" respond to certain inputs but lack memory or the capacity to draw lessons from the past to guide present judgements. IBM's Deep Blue chess-playing computer is an illustration of this kind. AI systems with limited memory are capable of drawing conclusions from the past and only remembering a limited amount of prior encounters. Self-driving automobiles that watch and make judgements based on current data are examples of this kind of technology. Theory of Mind, humans may communicate socially with AI systems because they comprehend human emotions, opinions, and thoughts. Most of this kind of AI is theoretical, and research is still being done to further it. Finally, Self-aware AI systems are conscious and self-aware. This kind of artificial intelligence, however, is yet purely theoretical and unrealized.

Artificial Intelligence (AI) has multiple basic forms based on application and techniques which is Machine Learning (ML), Deep Learning, Natural Language Processing (NLP), Robotics, Expert Systems, Computer Vision, and Fuzzy Logic. Subfields of machine learning (ML) include reinforcement learning, unsupervised learning, semi-supervised learning, and supervised learning. Applications such as fraud detection, spam filters, and personalised recommendations use it. Image and audio recognition, as well as natural language processing, are applications of deep learning, a subset of machine learning that uses multi-layered neural networks. NLP, or natural language processing, is the study of AI systems that can comprehend, translate, and produce natural language. Sentiment analysis, chatbots, and language translation services are a few examples. In robotics, artificial intelligence is incorporated into robots to carry out tasks that call for physical motions. Examples of these robots include industrial robots, robotic hoover cleaners, and medical robots. Expert systems, which are artificial intelligence (AI) systems that simulate human experts' decision-making processes, are employed in financial trading and medical diagnostic applications. Computer vision refers to artificial intelligence (AI) systems that analyse and decide using visual data. Examples of these systems include autonomous cars, object detection, and facial recognition. Lastly, fuzzy logic is a type of logic that deals with approximate reasoning as opposed to fixed and accurate thinking. It is frequently utilised in decision-making systems in uncertain settings as well as control systems for appliances.

2.1.2 Supply Chain Management

A supply chain is a network of related entities, organisations, resources, activities, and technology that produce, distribute, and deliver products or services from suppliers to end users. It includes all of the procedures and processes necessary to get a product or service from raw materials to the hands of the end user.

Supply chain management is the coordination and optimisation of operations throughout the supply chain to maintain the smooth flow of goods or services, reduce costs, maximise efficiency, and successfully satisfy customer needs. It includes several operations such as procurement, production planning, inventory management, logistics, transportation, warehousing, and distribution.

To remain competitive in today's globalised and linked economy, organisations must implement effective supply chain management. To anticipate and respond to changes in demand, reduce risks, and adapt to changing market conditions, various supply chain stakeholders must collaborate, communicate, and coordinate.

Effective supply chain management (SCM) is crucial for improving company performance and customer happiness. Over the last 20 years, supply chains have become more complicated due to the dynamic interaction of many processes and structures. According to Arora and Gigras (2018), supply chain management is crucial for corporate success.

Author(s)	Definition
Bozarth (2008)	Supply Chain Management aims to maximise customer value and provide practical benefits by managing connections and activities throughout the supply chain.
Mentzer et al. (2001)	SCM involves the exchange of commodities, money, data, and services between providers and clients.
Grant et al. (2017)	Supply Chain Management integrates a company's and its suppliers' business operations to provide customers with information, commodities, and services that create value.
Misra (2018)	Supply Chain Management involves aligning policies and actions to ensure timely delivery of items to customers, minimise costs, and meet service standards.

Table 2.0 Supply Chain Management Definition

2.1.3 Adoption of Artificial Intelligence (AI)

Adoption of AI refers the process by which people, organisations, or society incorporate artificial intelligence technology into their operations, procedures, or daily activities. This adoption entails using AI technologies to complete activities, make choices, or supplement human talents in a variety of fields.

AI adoption may result in a variety of advantages, including increased productivity, better decision-making, cost savings, automation of repetitive processes, and the creation of creative goods or services. However, it also raises worries about data privacy, ethical implications, technological complexity, and the necessity for specialised individuals. Overall, AI adoption gives a tremendous opportunity for individuals, organisations, and society to capitalise on artificial intelligence's revolutionary potential to drive innovation, increase efficiency, and create value.

2.1.4 Artificial Intelligence (AI) Adoption in Supply Chain

Artificial intelligence (AI) adoption in the supply chain refers to the incorporation and use of AI technology and techniques into the different processes and activities involved in supply chain management. This covers AI applications in procurement, production planning, inventory management, logistics, transportation, warehousing, and distribution.

AI adoption in the supply chain comprises deploying AI-powered solutions to automate jobs, optimise processes, make data-driven choices, and improve overall supply chain efficiency and effectiveness. This may entail using AI algorithms, machine learning models, natural language processing, computer vision, robots, and other AI technologies to analyse data, anticipate trends, discover patterns, and optimise processes in real time.

For examples of AI adoption in the supply chain are predictive analytics. Using AI algorithms to analyse previous data and predict future demand, resulting in more accurate inventory planning and production forecasts. Next, supply chain optimisation.

Using AI algorithms to optimise supply chain networks, routes, and workflows in order to reduce costs, shorten lead times, and improve overall efficiency.

Overall, AI adoption in the supply chain aims to use artificial intelligence to streamline operations, boost efficiency, lower costs, improve customer satisfaction, and gain a competitive advantage in a fast changing business landscape.

2.2 Theoretical Framework Development

The process of developing a theoretical framework entails creating a conceptual framework that directs research activities and serves as a lens through which things are perceived and examined. Fundamentally, it incorporates existing theories, ideas, and models to provide insights into the fundamental mechanisms regulating a given occurrence and to clarify the connections between variables. To find important theoretical stances and concepts that are relevant to the study subject, this procedure comprises a careful reading of related literature. In a particular field of study, the theoretical framework helps in the design of research hypotheses as well as the interpretation of results and the creation of new knowledge. It also acts as a guide for researchers, offering a framework for comprehending the complexity of the phenomena they are studying and direction for their questions.

2.2.1 Theory

The study's underlying the theory holds that a complex interaction of organisational, technological, and external variables affects how artificial intelligence (AI) is used in the supply chain sector. The study makes the following assumptions about the adoption patterns of artificial intelligence (AI) in supply chains: technological readiness, organisational culture and readiness, leadership support, resource availability, regulatory environment, and market dynamics. These theories are based on theories of innovation diffusion and organisational change. These variables interact in dynamic ways, impacting organisations' implementation plans and decision-making procedures as they negotiate the benefits and difficulties posed by AI integration.

2.2.2 Factors That Affects the Artificial Intelligence Adoption in Supply Chain (IV)

2.2.2.1 Technology

The technological context includes all of the technologies that the organisation currently uses, both internal and external, as well as any emerging technologies that might be pertinent to it and those that are currently available on the market but not yet being used by the business (Hwang, Huang & Wu,2016). Technology can include both tools and procedures. Current technologies play a critical role in the adoption process because they limit the scope and speed of technological change that a company may implement (Baker, 2012). According to Baker (2012), an organisation needs a strong IT infrastructure and personnel that are technologically adept in order for new technology adoption to be effective.

2.2.2.2 Organization

The company's components, including its size, resources, and management structure, are described in the organisational framework (Hwang, Huang & Wu, 2016). Nguyen and Petersen (2017) suggest that the adoption of ICT and firm size are inversely related. The adoption is significantly impacted by the size and scope of an organisation (Wang et al., 2003). Small and medium-sized businesses are more likely to adopt new ICTs than bigger, more rigid corporations because of their adaptability and speed of adjustment (Kilangi, 2012). The largest barrier to technology adoption, according to research using the TOE model to examine the factors impacting the adoption of IoT in China's agricultural supply chain, is cost (Lin, Lee & Lin, 2016). Technology resources were one of the other aspects (Pan & Jang, 2008).

2.2.2.3 Environment

According to Hwang, Huang, and Wu (2016), the environmental element is the setting in which a business works. This setting may include the business market, consumers, competitors, and the government. According to a review of earlier research, SMMEs in third-world nations use information technology due to competitive pressures (Jere & Ngidi, 2020). According to a research by Mariemuthu (2019), there is a favourable association between competitive pressure and AI adoption in banking organisations. Similarly, Li's (2008) study showed that external reinforcement and competitive pressures had a major impact on manufacturing businesses' adoption of e-procurement. Teo, Lin, and Lai (2009) also discovered that trade partners had a big impact on e-procurement adoption.

2.2.3 Adoption of Artificial Intelligence (AI) in Supply Chain (DV)

The adoption of artificial intelligence (AI) is the dependent variable in studies examining its application in the supply chain. This indicates that the goal of research is to comprehend and provide an explanation for the occurrence or outcome. The degree to which supply chain industry organisations incorporate AI technology into their operations is represented by the dependent variable in this context, which is AI adoption.

Examining several aspects that affect an organization's decision to embrace AI and how much of it means exploring the adoption of AI. To find patterns, correlations, and causal links that explain why certain organisations embrace AI more quickly or efficiently than others, researchers usually look into these characteristics. The dependent variable (AI adoption) is generally the main focus of research on AI adoption in the supply chain, helping to explain the motivations for, difficulties encountered, and results of integrating AI technology into supply chain management procedures. The dependent variable (AI adoption) is generally the main focus of research on AI adoption in the supply chain, helping to explain the motivations for, difficulties encountered, and results of integrating AI technology into supply chain management procedures.

2.2.4 Theoretical Framework

A multifaceted set of factors influences the adoption of artificial intelligence (AI) in supply chain management, which can be classified as technological readiness, leadership commitment, the presence of a data science and AI workforce, competitive pressure, and customer demand. This theoretical framework offers a systematic way to comprehending how these variables interact and contribute to the effective integration of AI technology into supply chains.

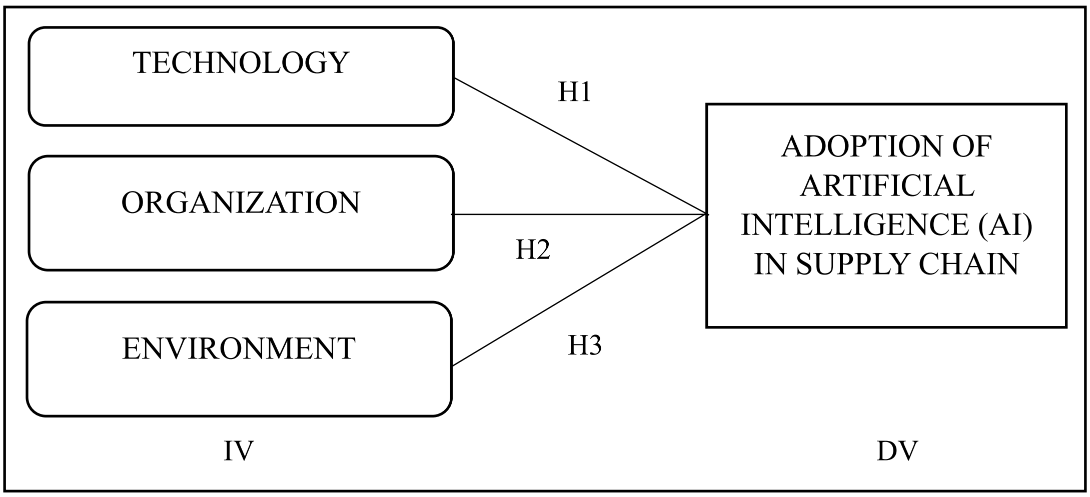

Figure 2.0 Theoretical Framework

2.2.5 Hypothesis

H1: Technology factor is one of the factors that affects the artificial intelligence adoption in supply chain.

AI solutions must provide a distinct advantage over current practices, such as increased effectiveness, precision, and financial savings. Businesses are more inclined to use AI in their supply chain if they believe it offers a substantial proportional benefit over conventional procedures. Adoption may be impacted by perceptions of difficulties in comprehending and applying AI technologies. The adoption of AI technology in supply chains is adversely affected by their perceived complexity. AI technology must work with the organization's current systems, procedures, and values. The possibility of AI technologies being used in supply chains increases with how well-suited they are to the systems and procedures in place now.

H2: Organization factor is one of the factors that affects the artificial intelligence adoption in supply chain.

Support from Top Management, adoption of AI depends on top management support and commitment. Adoption of AI in supply chains is strongly impacted by strong top management support. Organisational Readiness, this refers to having the required assets, including money, trained labour, and IT infrastructure, available. Adoption of AI in supply chains is facilitated by increased organisational preparedness. Size of Organisation, bigger companies are more likely to have greater resources and to be in a better position to implement new technology. AI technologies are more likely to be implemented in supply chains by larger companies.

H3: Environment factor is one of the factors that affects the artificial intelligence adoption in supply chain.

Competitive Pressure, organisations may embrace AI to preserve or improve their competitive edge depending on the amount of pressure they face from rivals. The use of AI in supply chains is favourably impacted by increased competition. Government rules and laws, as well as the regulatory environment, can help or hurt the adoption of AI technology. Adoption of AI in supply chains is positively impacted by a regulatory framework that is friendly. An organization's choice may be influenced by its supply chain partners' preparedness to accept and use AI technology. The adoption of AI in supply networks is positively impacted by parties in the chain being more prepared.

2.3 Summary

In conclusion, many important aspects impact the use of artificial intelligence (AI) in supply chain management. Technological readiness, leadership commitment, workforce competency in data science and AI, and competitive pressure/customer demand all influence the adoption landscape. Companies with excellent technology infrastructure, strong leadership support, talented workers, and a proactive approach to market dynamics are better positioned to successfully integrate AI into their supply chains. Understanding and resolving these challenges is critical for firms looking to use AI to improve efficiency, responsiveness, and competitiveness in the ever-changing world of supply chain management.

CHAPTER 3

RESEARCH METHODOLOGY

3.0 Introduction

The systematic, theoretical analysis of the procedures used in a field of study is known as research methodology. It includes the guidelines, protocols, and methods that help researchers gather, process, and evaluate data. In essence, research methodology serves as a road map for data collection, measurement, and analysis, offering a precise route to accomplishing the study's goals.

3.1 Research Design

This study's quantitative methodology reflected the social sciences' dominant research structure. The focus of quantitative research was on gathering and analysing numerical data, which was essential for achieving the study's goals. While some data had numerical structures imposed by applying scales or coding techniques to category replies, other data were intrinsically quantitative, such as numerical variables that were directly measured or seen. The researchers were able to do statistical studies ranging from simple descriptive approaches to intricate inferential models thanks to this methodical approach. By using these techniques, data could be gathered, patterns could be found, correlations between variables could be shown, and important factors could be compared.

This study's quantitative methodology played an essential role in methodically collecting and evaluating numerical data to identify the variables affecting the supply chain's adoption of artificial intelligence. The main method of gathering data was the use of structured questionnaires, which guaranteed the replies' dependability and consistency. The information gathered using this method marked the key elements influencing AI adoption and made it easier to assess the correlations between variables. The study gave strong insights into the dynamics of AI integration in supply chains by utilising quantitative approaches, opening the door for suggestions based on solid facts and well-informed decision-making in the industry.

3.2 Data Collection Methods

Data for this study were gathered using the method of quantitative analysis. The quantitative study used methods including research, polls, and planned observations. In order to identify the most important element influencing the adoption of artificial intelligence in the supply chain, data was gathered for this study using a questionnaire. A scale with 1 indicating strongly disagree, 2 disagree, 3 neutral, 4 agree, and 5 strongly agree was used to assess the respondents' responses to each topic.

A questionnaire was a list of printed or written enquiries designed to gather data from participants. In order to get information from responders, this data collecting tool used a series of questions as well as other prompts. The open-ended and closed-ended questions were designed to gather specific data on a certain topic. Respondents completed the majority of surveys on their own, without the help of an interviewer.

3.3 Sampling Strategy

The study's participants included all supply chain companies that had made some use of artificial intelligence (AI). This covered companies who had already adopted AI technology, those that were engaged in the process, and those that had thought about utilising AI but had not yet done so. Among the many groups that made up the population were retail companies. The research aimed to give a comprehensive picture of AI adoption throughout the supply chain ecosystem by concentrating on these groups, making sure that the findings applied to all parties participating in these crucial procedures.

The sample frame was carefully developed to guarantee that it accurately reflected the intended population. This entailed compiling a list of possible responders from dependable sources such industry directories, supply chain-related professional associations, and corporate databases. By offering a large and reliable population of supply chain and retail participants, these sources raised the possibility that the sample was both representative and complete. By using these trustworthy lists, the study made sure that all relevant supply chain industry segments were covered, supporting the validity and dependability of the research findings.

The sampling procedure began with stratification, in which the population was separated into several subgroups or sectors according to significant attributes. The categories comprised the industrial sector such as retail, the level of AI adoption (early adopters, late adopters, and non-adopters), and the size of the organisation (small, medium, or big based on revenue or personnel count). Random sampling was carried out inside every group once the population had been stratified. This method allowed for a more thorough and in-depth investigation across a range of demographic segments by guaranteeing that each subgroup was fairly represented in the final sample. The study's capacity for estimating data was improved by the application of the stratified random sampling technique, which also gave researchers a more comprehensive grasp of the patterns in AI use in the supply chain industry.

Achieving results that were both statistically significant and widely applicable required careful consideration of sample size. The sample size was found to be enough to guarantee that the statistical analysis generated significant insights and offered a trustworthy representation of the population which is N = 80. When determining the sample size, consideration was given to variables such the expected level of population variability, the required level of accuracy, and the degree of confidence. The study's credibility and influence were increased by carefully choosing the sample size to guarantee that its findings were solid and applicable to a wider population.

To ensure the sample's relevance and improve it, certain inclusion and exclusion criteria were developed. Companies who have either considered, tried, or effectively adopted AI had to satisfy the supply chain industry's inclusion standards. This requirement made sure that each participant had some connection to the goals of the study. According to the exclusion criteria, companies who were not involved in the supply chain sector or had no interest in using AI were not included. This focused selection made sure that data from companies utilising AI in the supply chain context were included in the research while preserving the study's relevance and specificity. By adhering to these rules, the research was able to generate accurate and useful data that was relevant to the target audience.

3.4 Data Analysis

The initial round of data collection involved sending structured questionnaires to a specific group of retail companies. These surveys were carefully designed to gather relevant data on AI adoption, featuring simple and concise questions to ensure accurate responses. Established criteria were applied to select the targeted organizations, ensuring they represented the broader demographic of interest. To enhance response rates and build a robust dataset, follow-up reminders were utilized. Participants were contacted through phone, email, or other communication methods to encourage survey completion. These follow-ups were strategically timed and included multiple reminders to maximize participation without overburdening respondents.

After collecting the survey responses, the data were meticulously entered into a database or spreadsheet and converted into a digital format for ease of analysis. The researcher leveraged automated tools to streamline this process, ensuring efficiency and minimizing errors.

For data analysis, the researcher employed **SPSS version 29**, widely recognized for its advanced statistical analysis capabilities. Exploratory Factor Analysis (EFA) was conducted to identify the underlying factors influencing AI adoption in the supply chain. During the data cleaning phase, surveys with significant missing data were identified and excluded to maintain the dataset's integrity. This process was critical to avoid uneven outcomes or erroneous conclusions. Outliers, which significantly deviated from the dataset, were identified and analyzed for potential causes, such as errors in data entry or unique circumstances within specific organizations. By addressing outliers, the researcher enhanced the dataset's quality, ensuring the findings were both accurate and reliable.

To facilitate consistent analysis, standardizing responses was prioritized, particularly for categorical data. For example, firm size, if used as a variable, was consistently categorized across surveys. This standardization reduced variability from differing interpretations or formats, thereby improving the data's dependability and comparability. Through systematic data collection, cleaning, and preparation, combined with robust statistical tools like SPSS 29 and EFA, the researcher ensured that the study's findings were based on high-quality, reliable data. This rigorous approach provided the foundation for generating accurate and meaningful insights into the adoption of AI in the supply chain sector.

3.5 Summary

Using a methodical and quantitative approach, this study was aimed at investigating how artificial intelligence (AI) is being used in the supply chain industry. The methodology was created to guarantee accurate data collection and analysis, functioning as a guide for accomplishing the goals of the study. Targeted retail businesses received structured surveys with an emphasis on clear, basic questions to ensure accurate answers. While data cleaning procedures dealt with missing data, outliers, and inconsistencies to preserve dataset integrity, strict follow-up procedures were used to optimize participation.

In order to identify the factors impacting AI adoption, the study used Exploratory Factor Analysis (EFA) and SPSS version 29 for advanced statistical analysis. By classifying participants according to industry type, level of AI utilisation, and organizational size, categorised random sampling guaranteed varied representation. This method offered thorough insights on trends in AI integration. To find relationships and patterns, data analysis required defining responses for reliability and consistency. Relevance and specificity were guaranteed by the research's thorough inclusion and exclusion criteria. Informed decision-making in the supply chain industry's AI adoption environment was supported by the creation of significant insights made possible by this methodical approach in conjunction with sophisticated tools such as SPSS and EFA.

CONCLUSION

Using the Technology-Organization-Environment (TOE) framework as a guide, this study concludes by thoroughly examining the many aspects impacting the adoption of Artificial Intelligence (AI) in supply chain management. The study emphasises the critical roles played by organisational preparedness, competitive challenges, and regulatory settings, as well as technical advantage. Organisations may successfully incorporate AI technology if they address these problems with a solid IT infrastructure, strong leadership support, and smart regulatory navigation. This integration is expected to boost overall competitiveness in the supply chain sector, optimise decision-making procedures, and increase operational efficiency. The results provide practitioners and policymakers with insightful information and practical suggestions for advancing innovation and improving supply chain management through the use of AI.

To sum up, this research has examined the many aspects that impact the integration of Artificial Intelligence (AI) in supply chain management, applying the Technology-Organization-Environment (TOE) framework. It has brought attention to the crucial roles that organisational preparation, technological readiness, and external environmental factors play in influencing the success of AI adoption. The results underscore how crucial it is that AI solutions are deemed reasonable in complexity, compatible with present systems, and provide a demonstrable advantage over current techniques. In particular, for larger organisations with more investment capability, organisational variables including trained individuals, availability of resources, and backing from senior management are critical. External factors that encourage the use of AI include partner preparedness, favourable regulatory frameworks, and competitive pressures.

In conclusion up, this study uses a quantitative research technique to assure dependability and thoroughness while carefully examining the factors impacting the adoption of AI across the supply chain sector. Through a methodical process of data collection and analysis using stratified random sampling and structured questionnaires, the research finds critical elements including organisational support, competitive pressures, and regulatory frameworks in addition to technology preparedness. These results highlight how important IT infrastructure, a trained labour force, and leadership dedication are to the development of effective AI integration. Additionally, the study offers insightful empirical support and useful suggestions that can enable stakeholders to improve decision-making procedures, boost operational effectiveness, and increase overall competitiveness. These insights will be crucial in the future for directing the strategic use of AI and driving ongoing innovation across the supply chain.

CHAPTER 4

DATA ANALYSIS

4.0 Introduction

In this chapter, the researcher describes the methodology and statistical tools used to analyse the data gathered during the study. The analysis uses SPSS version 29, which includes numerous critical techniques such as descriptive analysis, reliability analysis, and multiple regression analysis. These methodologies are critical for investigating the factors influencing Artificial Intelligence (AI) adoption in the supply chain, as indicated in the study's theoretical framework. Using these analytical techniques, the researcher hopes to give a comprehensive understanding of how factors influence Artificial Intelligence (AI) adoption. The chapter also focusses on evaluating the conclusions from these investigations, which provide important insights for the supply chain business.

To assure the data's dependability and clarity, a quantitative research methodology was used, with questionnaires serving as the major data gathering tool. A pre-test of the questionnaire was undertaken to ensure its reliability and simplicity of comprehension by respondents. This data analysis includes reliability analysis as well as multiple regression analysis. Visual aids such as tables, pie charts, and bar charts are used throughout the chapter to improve the clarity and presentation of the findings, making them more accessible and helpful to readers. This chapter provides as a foundation for comprehending the empirical parts of the study, linking theoretical discoveries to practical consequences.

4.1 Pilot Test Analysis

A pilot test is an important step in ensuring the reliability and validity of research equipment. In this study, the pilot test was conducted after the first questionnaire had been prepared but before it was given to the primary set of respondents. The goal was to evaluate the questionnaire's clarity, reliability, and validity. A total of 30 respondents in retail industry took part in the pilot test, offering input and replies that helped the researcher modify the questionnaire and establish its applicability for the bigger study.

The key reliability metric used in the analysis of the pilot test data was Cronbach's alpha. Cronbach's alpha is a widely recognized reliability coefficient that assesses the internal consistency of a group of items on a scale, evaluating how closely related these items are to one another. Cronbach's alpha can vary from 0 to 1, with higher values suggesting more dependability. According to Sekaran's (2003) recommendations, Cronbach's alpha values less than 0.60 are regarded bad, values between 0.70 and 0.80 are acceptable, and values more than 0.80 indicate strong dependability. In this pilot study, Cronbach's alpha values were examined to determine that the questionnaire satisfied these requirements, laying the groundwork for the major study.

Gopal and Misra (2017) used a similar technique to pilot testing in their research of customer satisfaction in the retail industry. Prior to full-scale data collecting, they ran a pilot test with 40 respondents to assess the survey instrument's reliability and intelligibility. Cronbach's alpha scores in their study varied between 0.75 and 0.85, indicating the questionnaire's reliability. Their findings emphasised the significance of pilot testing in improving research instruments and assuring the quality of obtained data. This highlights how pilot testing is a critical stage in different businesses, including retail, to improve the reliability of research findings.

Alpha Coefficient Range	Strength of Association
α < 0.6	Poor
α = 0.6 to 0.7	Moderate
α = 0.7 to 0.8	Good
α = 0.8 to 0.95	Very Good
α > 0.95	Excellent

Table 4.0 The Standard Coefficient Alpha

4.1.1 Cronbach's Alpha Coefficient for pilot testing.

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.964	.965	18

Table 4.1 Cronbach's Alpha for Pilot Test

Table 4.1.1 summarises the reliability test findings, which show that variables are consistent across all three factors which is technology, organisation, and environment. These factors were deliberately chosen to examine their impact on the implementation of Artificial Intelligence (AI) in supply chain management. The pilot test has a Cronbach's alpha coefficient of 0.964, which falls well inside the "very good" reliability category. This high result indicates that the questionnaire questions are internally consistent and tightly connected, assuring the reliability of the data gathering instrument.

The pilot test included 18 items, all of which were determined to fulfil the requisite dependability levels. This ensures that the questionnaire is suitable for moving on with the main part of the research. The favourable findings of the pilot test verify the instrument's form and content, proving that it can efficiently gather the data required to analyse AI adoption in supply chains. Encouraged by these findings, the researcher went on to gather data from the intended respondents in the main study. The pilot test findings established a solid foundation for confidence in the instrument's capacity to produce significant and reliable results in the larger research effort.

4.2 Descriptive Analysis

This part focusses on the demographic data collected via the questionnaire, offering an overview of the respondents' characteristics and perspectives on Artificial Intelligence (AI). Gender, age, race, job category, and years of experience in their present capacity are some of the demographic factors. By analysing these aspects, the researcher hopes to gain a thorough grasp of the respondents' experiences and relevance to the study. In addition to demographic information, the questionnaire asks specific questions on the respondents' knowledge with AI. These questions ask respondents whether they are aware of AI technology and whether AI is now being used in their employment. This data is critical for determining the degree of AI exposure among participants and evaluating the level of AI adoption across various organisational contexts.

The descriptive analysis allows the researcher to summarize the acquired data using statistical approaches such as frequency distributions, percentages, and graphical representations like charts and tables. These tools give a concise and clear snapshot of the respondents' attributes, making the data easy to comprehend. By analysing this demographic and AI-related data, the researcher may reveal patterns, detect potential biases, and provide an outline for deeper analysis in later stages of the study.

	N Statistic	Minimum Statistic	Maximum Statistic	Mean Statistic	Std. Deviation Statistic
Gender	88	1	2	1.40	.492
Age	88	1	5	2.81	.800
Race	88	1	4	1.61	.808
Job Category	88	1	5	3.41	1.141
Years of Current Role	88	1	4	1.99	.669
Do You Know about Artificial Intelligence (AI)?	88	1	2	1.05	.209
Did Your Workplace or Industry that You Work Now Implement Artificial Intelligence (AI)?	88	1	3	1.44	.692
Valid N (listwise)	88				

Table 4.2 Descriptive Analysis

An overview of the situational and demographic characteristics of the 88 respondents who took part in the study is given in the descriptive analysis table. It helps you understand the distribution and variability of the data by displaying important statistical indicators like the mean, standard deviation, minimum, and maximum for each variable. These factors include understanding of artificial intelligence (AI), workplace AI deployment, years in current role, gender, age, race, and job category.

The gender variable has a standard deviation of 0.492 and a mean of 1.40, with values coded as 1 for males and 2 for females. This implies that responders were somewhat more male. With a mean of 2.81 and a standard deviation of 0.800, the age variable, which is coded into five categories, shows that the majority of respondents are middle-aged, most likely between the ages of 25 and 34. With a mean of 1.61 and a standard deviation of 0.808, the race variable, which was categorised into four groups, shows that Malay respondents dominate, while Chinese, Indian, and 'Other' respondents are less represented.

According to the mean of 3.41 and the standard deviation of 1.141 for job categories classified from 1 to 5, respondents are more likely to be employed in middle-level positions like operations or warehouse workers than in higher-level positions like directors or CEOs. The majority of respondents are relatively new to their employment, with 2-4 years of experience being the most prevalent, according to the years of current role variable, which has a mean of 1.99 and a standard deviation of 0.669. According to these demographic data, the workforce is racially and age-diversified to a moderate degree, although it is biassed towards younger workers in mid-level operational positions.

The study's main focus is highlighted by the factors pertaining to AI awareness and implementation. The majority of respondents (1 for "Yes" and 2 for "No") reported being aware of AI, as evidenced by the mean of 1.05 and the extremely low standard deviation of 0.209. However, the workplace AI implementation, which is categorised into three replies (1 being "Yes," 2 being "No," and 3 being "Not Sure"), has a mean of 1.44 and a standard deviation of 0.692. This demonstrates that even though AI has been implemented in many companies, a sizable percentage of respondents are either unaware of its use or operate in settings with low adoption rates.

4.2.1 Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	53	60.2	60.2	60.2
	Female	35	39.8	39.8	100.0
	Total	88	100.0	100.0	

Table 4.3 Respondent's Gender

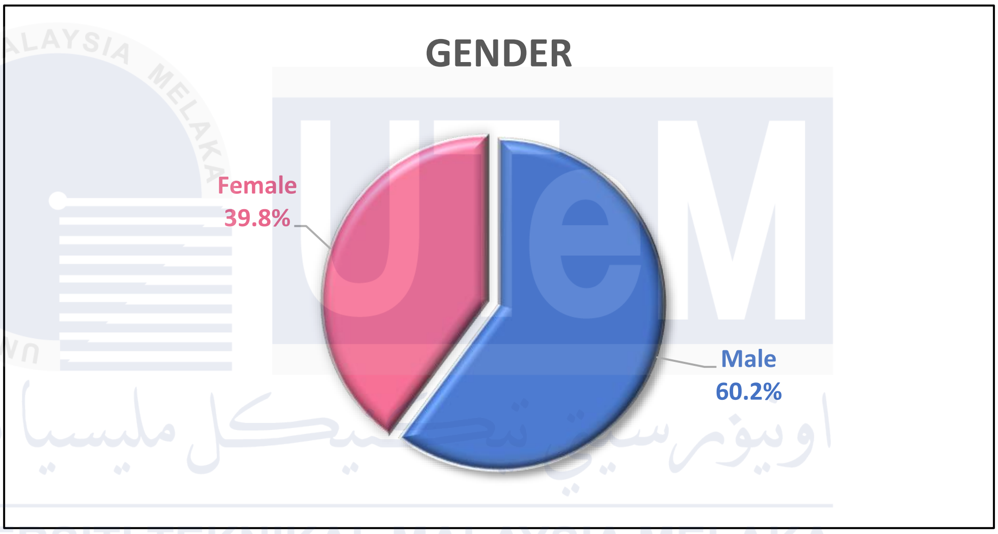

Figure 4.0 Respondent's Gender

Table 4.3 and Figure 4.0 shows the gender of the respondents. Based on the table and the pie chart, we can see that from 88 respondents, the frequency of male is 53 with percentage 60.2% and frequency of female is 35 with percentage 39.8%. From here, we can conclude that the frequency of male is more than the female that participated in this survey.

4.2.2 Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 18 years	1	1.1	1.1	1.1
	18 – 24 years	32	36.4	36.4	37.5
	25 – 34 years	41	46.6	46.6	84.1
	35 – 44 years	11	12.5	12.5	96.6
	Above 44 years	3	3.4	3.4	100.0
	Total	88	100.0	100.0	

Table 4.4 Respondent's Age

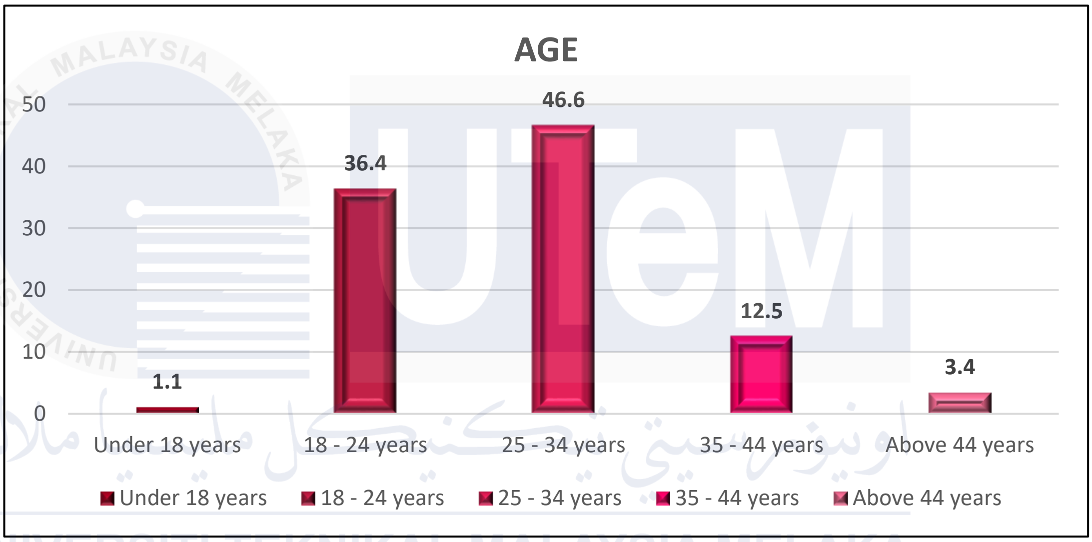

Figure 4.1 Respondent's Age

As shown in Table 4.4 and Figure 4.1, the survey's 88 respondents were separated into five age groups, demonstrating diverse participation patterns. The youngest age group, under 18, had the lowest representation, with only one responder accounting for a measly 1.1% of the overall sample. Similarly, the age group over 44 years old had a poor participation rate, with only 3 responders representing 3.4% of the sample. The 35-44 age group had a significantly larger presence, with 11 responders (12.5% of retail companies participants). On the other side, the 25-34 age group had the highest participation rate, accounting for 41 respondents or 46.6% of the total, making it the survey's dominating demographic. Following closely, the 18-24 age group had 32 responds, which represents 36.4% of the total. These findings show that the most retail industry workers who participated in this study are young people, especially those aged 25-34, followed by those aged 18-24.

4.2.3 Race

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Malay	49	55.7	55.7	55.7
	Chinese	27	30.7	30.7	86.4
	Indian	9	10.2	10.2	96.6
	Other	3	3.4	3.4	100.0
	Total	88	100.0	100.0	

Table 4.5 Respondent's Race

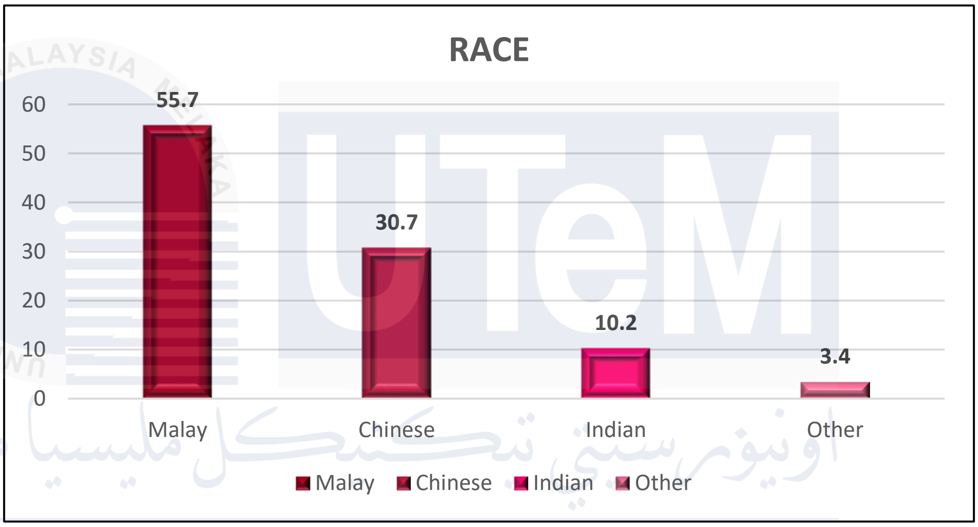

Figure 4.2 Respondent's Race

According to Table 4.5 and Figure 4.2, survey participants come from a variety of ethnic backgrounds, including Malay, Chinese, Indian, and Others races who work in retail. Malays made up most of these groups, with 49 out of 88 respondents, or 55.7% of the entire sample. This suggests that the Malay community was the most active in this poll. Following the Malays, the Chinese were the second-largest group, accounting for 30.7% of respondents, with 27 people working in retail enterprises contributing to the research. Indians were comparably under-represented, accounting for only 9 respondents (10.2% of the overall sample). Finally, the "Other" category, which includes ethnic groups such as Kadazandusun and Iban, had the least representation, with only three responders (3.4% of survey participants). These findings show the retail sector's variety while also reflecting the demographic composition of its workers.

4.2.4 Job Category

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	CEO / Director	2	2.3	2.3	2.3
	Manager / Supervisor	23	26.1	26.1	28.4
	Operation / Technical	17	19.3	19.3	47.7
	Warehouse Staff	29	33.0	33.0	80.7
	Other	17	19.3	19.3	100.0
	Total	88	100.0	100.0	

Table 4.6 Respondent's Job Category

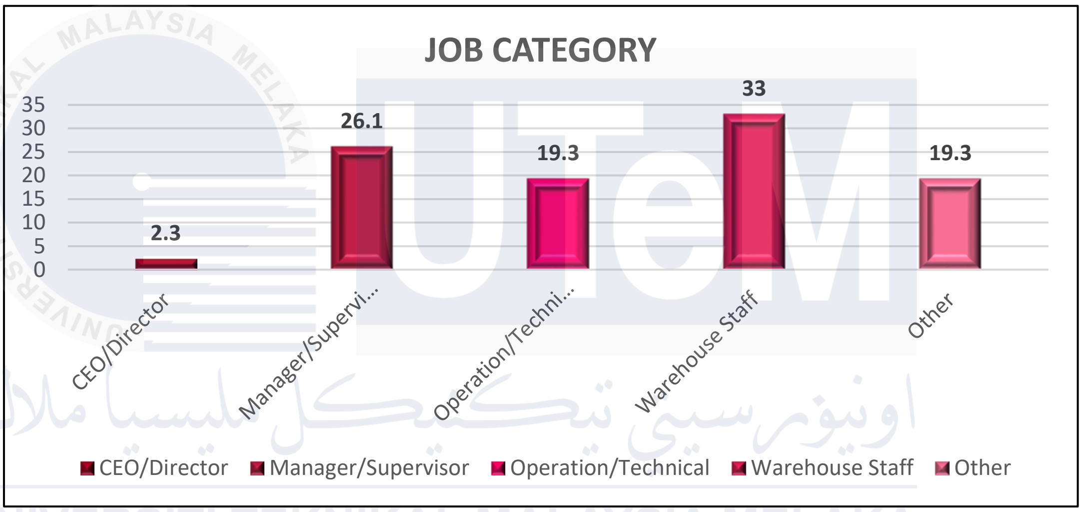

Figure 4.3 Respondent's Job Category

Table 4.6 and Figure 4.3 show the distribution of respondents according to their job categories, highlighting their involvement in the retail business. CEOs or Directors had the lowest representation among the 88 responses, accounting for only two persons or 2.3% of the total. This suggests that higher-level executives took little part in the poll. Managers or supervisors are a major category, with 23 respondents (26.1% of the total). This shows that mid-level management is well represented in the data, which might provide insights into retail decision-making and supervisory positions. Operation or technical staff, as well as warehouse workers, play an important role. Both groups had 17 and 29 responders, which represent 19.3% and 33.0%, respectively. The high frequency of workers in warehouses shows the operational backbone of retail businesses and their vital role in day-to-day logistics. Finally, the "Others" group has 17 responders, accounting for 19.3%.

4.2.5 Years of Current Roles

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0 – 1 years	17	19.3	19.3	19.3
	2 – 4 years	58	65.9	65.9	85.2
	5 – 7 years	10	11.4	11.4	96.6
	Above 7 years	3	3.4	3.4	100.0
	Total	88	100.0	100.0	

Table 4.7 Respondent's Years of Current Role

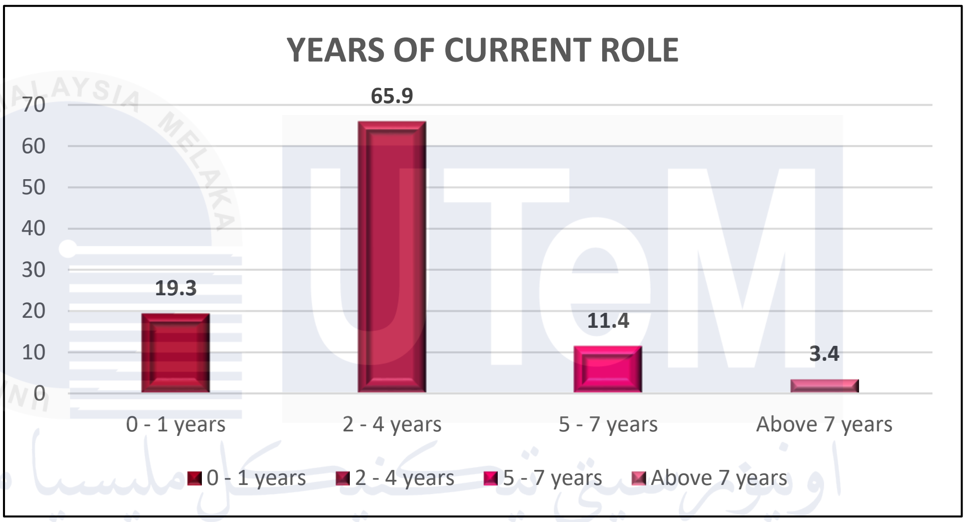

Figure 4.4 Respondent's Years of Current Role

Table 4.7 and Figure 4.4 show the distribution of respondents by years of experience in their current position in the retail business. Among the 88 responses, those with less than two years of experience make up 19.3% of the sample, with 17 being into this group. This demonstrates the presence of relatively new personnel in the sector. The largest category is made up of responders with 2-4 years of experience, which accounts for 58 people or 65.9% of the total. This significant percentage shows that the most the retail labour consists of persons with moderate experience, indicating job stability and growth. Respondents with 5-7 years of experience are a smaller group, with 10 participants totalling 11.4% of the total. Finally, individuals with more than 7 years of experience make up the lowest category, with only 3 replies, or 3.4%. This low percentage may imply that long-term retention in specialised retail positions is rare, potentially owing to professional advancement or migrations to other industries.

4.2.6 Do You Know about Artificial Intelligence (AI)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	84	95.5	95.5	95.5
	No	4	4.5	4.5	100.0
	Total	88	100.0	100.0	

Table 4.8 Respondent's awareness about Artificial Intelligence (AI)

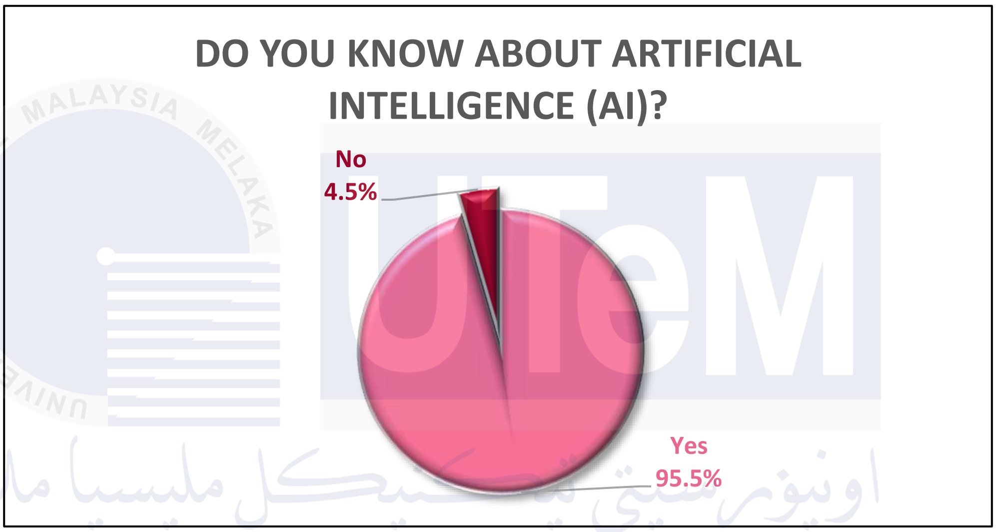

Figure 4.5 Respondent's awareness about Artificial Intelligence (AI)

Table 4.8 and Figure 4.5 show respondents' awareness of artificial intelligence (AI). Out of 88 individuals, 84 (95.5%) said they were aware of AI. This high rate shows that retail employees are well-versed in AI principles. In comparison, only four respondents, or 4.5%, said they were unaware of AI. This low proportion indicates that a lack of understanding regarding AI is rather rare among the studied population. The high degree of AI knowledge might be linked to the growing importance of AI technology in a variety of industries, including retail, where automation and data-driven solutions are being used to improve efficiency and consumer experiences. These results underscore the importance of AI as a topic of interest and relevance in the retail industry.

4.2.7 Did Your Workplace or Industry that You Work Now Implement Artificial Intelligence (AI)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	59	67.0	67.0	67.0
	No	19	21.6	21.6	88.6
	Not Sure	10	11.4	11.4	100.0
	Total	88	100.0	100.0	

Table 4.9 Respondent's Workplace Implement Artificial Intelligence (AI) or Not

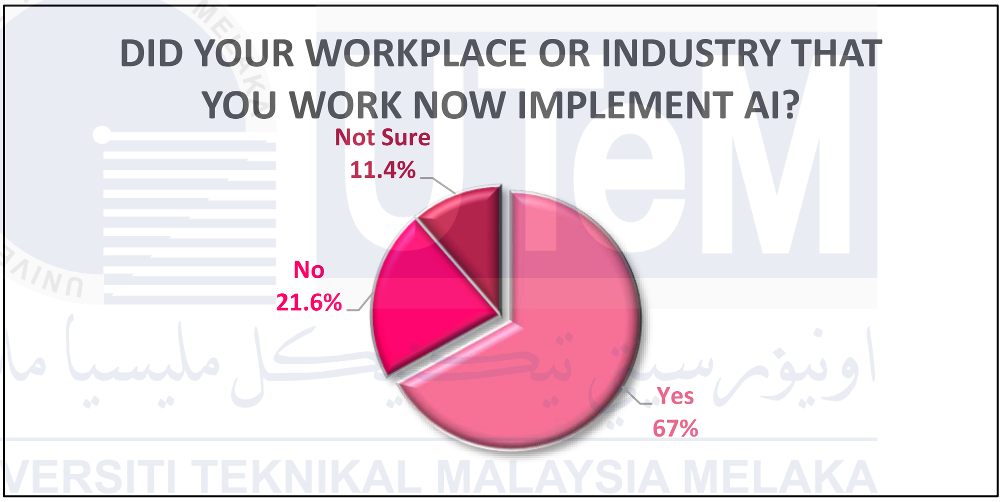

Figure 4.6 Respondent's Workplace Implement Artificial Intelligence (AI) or Not

Table 4.9 and Figure 4.6 show whether respondents' organizations have adopted artificial intelligence (AI). Among the 88 respondents, 59 (67.0%) indicated that their organizations use AI. This demonstrates a high degree of AI use in the retail industry, showing the increased integration of technology to improve operational efficiency and decision-making processes. On the other side, 19 respondents (21.6%) claimed that their employers had not incorporated AI. This shows that, while adoption is broad, certain organizations in the sector may have yet to embrace AI technology, either owing to financial restrictions, a lack of experience, or a lack of understanding of their benefits. In addition, 10 respondents, or 11.4%, were unclear whether AI was being used in their business. This confusion may indicate a lack of communication or understanding inside organizations about the deployment and usage of AI techniques.

4. 3 Reliability Analysis

This process determines if the survey data is reliable for the research. Cronbach's alpha is a well-known dependability coefficient that evaluates how strongly elements in a collection are positively connected to one another, as stated by Nunnally and Bernstein (1994). The researcher employed this test after doing a descriptive analysis on the demographic data to assess the consistency and reliability of the study's variables. Reliability is crucial in research because it assures that the results remain consistent over time and appropriately reflect the whole population under study. According to Tavakol and Dennick (2011), dependability is attained when a study's results can be replicated using identical procedures, indicating that the research instrument is reliable. Cronbach's alpha was used as an extra test in this study to assess the quality of the data collected. This measure is particularly valuable for determining internal consistency, which ensures that all elements on a scale contribute significantly to the construct under consideration. A high Cronbach's alpha value indicates good dependability, making it an important tool for validating the robustness of the data and establishing the framework for future analysis in research.

Alpha Coefficient Range	**Strength of Association**
α < 0.6	Poor
α = 0.6 to 0.7	Moderate
α = 0.7 to 0.8	Good
α = 0.8 to 0.95	Very Good
α > 0.95	Excellent

Table 4.10 The Standard Coefficient Alpha Range and Its Strength of Association

Case Processing Summary

		N	%
Cases	Valid	88	100.0
	Excluded[a]	0	.0
	Total	88	100.0

a. Listwise deletion based on all variables in the procedures

TECHNOLOGY FACTOR (IV 1)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.974	.975	6

Table 4.11 Cronbach's Alpha Reliability Coefficient for Technology Factor (IV1)

The Cronbach's Alpha value of the technology factor (IV1) is 0.974, based on six measurement items. This high value indicates excellent internal consistency and reliability among the items used to measure the technology factor. Additionally, the Cronbach's Alpha based on standardized items is 0.975, reinforcing the strong coherence of these items. Generally, a Cronbach's Alpha value above 0.70 is considered acceptable, while values above 0.90 indicate superior reliability. Therefore, the result of 0.974 demonstrates that the scale effectively captures the underlying construct of the technology factor without significant measurement error. This high reliability suggests that the items are highly correlated and provide consistent responses across different observations. Consequently, the measurement instrument used for this factor is deemed robust and can be confidently applied in future analyses or research related to the impact of technology in the study's context.

ORGANIZATION FACTOR (IV 2)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.936	.936	6

Table 4.12 Cronbach's Alpha Reliability Coefficient for Organization Factor (IV2)

The Cronbach's Alpha value for the organization factor (IV2) is 0.936, based on six measurement items. This result indicates excellent internal consistency and reliability among the items used to measure this factor. The Cronbach's Alpha based on standardized items is also 0.936, which reinforces the consistency of these results. In general, Cronbach's Alpha values above 0.70 are considered acceptable, and values exceeding 0.90 demonstrate superior reliability. Therefore, the obtained value of 0.936 strongly suggests that the items in this scale are well-correlated and measure the organization factor cohesively. This high level of reliability signifies that the measurement instrument effectively captures the organizational constructs being assessed without significant measurement errors. As a result, researchers can confidently rely on the organization factor scale for accurate and consistent data collection, enhancing the validity and robustness of analyses involving organizational elements in the study.

ENVIRONMENT FACTOR (IV 3)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.939	.940	6

Table 4.13 Cronbach's Alpha Reliability Coefficient for Environment Factor (IV3)

The Cronbach's Alpha value for the environment factor (IV3) is 0.939, based on six measurement items, with a slightly higher value of 0.940 based on standardized items. This high alpha score signifies excellent internal consistency and reliability, indicating that the items used to measure the environment factor are strongly correlated and provide consistent responses. Typically, Cronbach's Alpha values above 0.70 are deemed acceptable, while values exceeding 0.90 demonstrate superior reliability. Thus, the obtained value of 0.939 suggests that the measurement scale effectively captures the underlying construct of the environment factor without significant measurement errors. This result reinforces the robustness of the measurement instrument in capturing environmental influences within the study. With such a strong reliability coefficient, the scale can be confidently used for future data collection and analysis, ensuring that responses reliably reflect variations in environmental factors relevant to the research context.

ARTIFICIAL INTELLIGENCE ADOPTION IN SUPPLY CHAIN (DV)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.964	.967	6

Table 4.14 Cronbach's Alpha Reliability Coefficient for Artificial Intelligence Adoption in Supply Chain (DV)

The Cronbach's Alpha value for the artificial intelligence (AI) adoption in the supply chain (DV) is 0.964, based on six measurement items, with a slightly higher value of 0.967 based on standardized items. This exceptionally high reliability score indicates excellent internal consistency among the items used to assess AI adoption in the supply chain. Generally, Cronbach's Alpha values above 0.70 are considered acceptable, while values exceeding 0.90 signify superior reliability. The results demonstrate that the scale effectively captures the construct of AI adoption in supply chains without significant measurement errors. The high correlation among the items indicates that respondents provided consistent responses across the different dimensions measured. This strong reliability validates the robustness of the measurement instrument, ensuring that it can accurately and consistently capture variations in AI adoption levels across different contexts or research samples. Consequently, this scale provides a solid foundation for analyzing the role of AI in supply chain processes and supports the validity of any conclusions drawn from the study findings.

TECHNOLOGY (IV1) + ORGANIZATION (IV2) + ENVIRONMENT (IV3)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.970	.971	18

Table 4.15 Cronbach's Alpha Reliability Coefficient

Using the 18 questions created from the identified factors, the researcher used a Likert scale to adequately quantify respondents' impressions. According to Hair et al. (2010), a reduction in the dependability coefficient might imply that the items are not closely connected with one another. This emphasises the significance of assessing internal consistency to ensure that all items on the scale contribute to the construct being assessed. Table 4.10 shows the reliability coefficients for both the independent and dependent variables in this investigation. The findings show that the survey questions were completely genuine, with a validity rating of 100%. The Cronbach's alpha value is 0.970, suggesting that 97% of the questions are credible and appropriate for further investigation. The survey has 18 items that are evenly dispersed throughout the three categories under evaluation. The first factor, technology, has 6 items, the second factor, organization, likewise contains 6 items and the third factor, environment, contains 6 items. These findings support the dependability of all variables and related items, as indicated in Table 4.10. This high level of dependability guarantees that the survey instrument is resilient, setting the groundwork for useful data analysis and interpretation.

4.4 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) is a statistical method used in research to uncover the underlying structure of a set of observed variables. It finds hidden variables, or factors, that account for the patterns of covariances or correlations between the variables that are observed. EFA is especially helpful in situations when the researcher lacks an existing concept regarding the quantity or kind of factors influencing the variables being studied. EFA was carried out in order to determine the main factors impacting the supply chain industry's adoption of artificial intelligence (AI) and to guarantee the validity and reliability of the questionnaire data described in the study.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.758
Bartlett's Test of Sphericity	Approx. Chi-Square	4240.944
	df	279
	Sig.	<.001

Table 4.16 KMO and Bartlett's Test

The "KMO and Bartlett's Test" table offers crucial details for carrying out an exploratory factor analysis (EFA). By analysing the sample adequacy and the existence of correlations among variables, these tests determine if the data is suitable for factor analysis. The percentage of variance among variables that may be common variance and thus appropriate for factor analysis is indicated by the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, a statistic with a range of 0 to 1. Kaiser's classification places the sample in this instance into the "middling" group, with a KMO score of

0.758, indicating that it is moderately suitable for EFA. A value above 0.7 is usually considered acceptable, and this result shows that the variables are sufficiently connected to support factor analysis.

Another crucial metric for determining if the correlation matrix is an identity matrix is Bartlett's Test of Sphericity. Factor analysis would be improper if the matrix were an identity matrix, which would indicate that there are no correlations between the variables. With degrees of freedom (df) equal to 279 and a significance value less than 0.001, the table's Bartlett's test gives a significant approximate Chi-Square value of 4240.944. This highly significant result (< 0.05) suggests that the data is appropriate for factor analysis and that the correlations between the variables are not random. The findings of the KMO and Bartlett's Test taken together provide compelling evidence that moving further with EFA is suitable and that the dataset is sufficient to find deeper reasons. These steps are essential for guaranteeing the validity and reliability of the factor analysis procedure, which improves the study's resilience and the results' interpretability.

4.5 Hypothesis Testing

Hypothesis testing is an important step in this study because it determines whether the researcher's hypotheses are supported or rejected based on the data. This procedure assesses the associations between the independent and dependent variables in to determine their statistical significance. The dependent variable in this study is the use of Artificial Intelligence (AI) in the supply chain, whereas the independent variables include three major factors which is technology, organization, and environment.

For a hypothesis to be judged valid, the correlation between the variables must be statistically significant. The p-value must be less than 0.05, suggesting that the observed results are statistically significant and not a result of random chance. Furthermore, the R-value, which reflects the multiple correlation coefficients, assesses the strength of the linear correlation between independent and dependent variables. A greater R-value indicates a stronger correlation, implying a strong relationship between the variables under assessment. The hypothesis testing procedure entails methodically determining if the hypothesised relationships hold true. By evaluating each hypothesis, the researcher will be able to identify which factors have a substantial impact on the adoption of AI in supply chain operations. This analysis gives vital insights into the dynamics of AI adoption and contributes to the study's overall goals by supporting the theoretical framework and research assumptions.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.835[a]	.698	.687	.35195

a. Predictors: (Constant), EnvOrga, OrgaOrga, TechOrga

b. Dependent Variable: DVNew

Table 4.17 Model Summary for Hypothesis

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.042	3	8.014	64.697	<.001[b]
	Residual	10.405	84	.124		
	Total	34.447	87			

a. Dependent Variable: DVNew

b. Predictors: (Constant), EnvOrga, OrgaOrga, TechOrga

Table 4.18 ANOVA Result for Hypothesis

Coefficient[a]

Model		Unstandardized Coefficients		Unstandardized Coefficients Beta	t	Sig.
		B	Std. Error			
	(Constant)	.377	.339		1.114	.268
1	NewTech	.577	.092	.618	6.280	<.001
	NewOrga	.121	.080	.114	1.518	.133
	NewEnv	.220	.129	.178	1.704	.092

a. Dependent Variable: DVNew

Table 4.19 Coefficients Result for Hypothesis

<u>Hypothesis 1</u>

H1: The technology factor is not significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

H0: The technology factor is significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

HA: H0 is accepted while H1 was rejected because the technology factor was significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

<u>Hypothesis 2</u>

H1: The organization factor is not significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

H0: The organization factor is significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

HA: H1 is accepted while H0 was rejected because the organization factor was not significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

<u>Hypothesis 3</u>

H1: The environment factor is not significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

H0: The environment factor is significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

HA: H1 is accepted while H0 was rejected because the environment factor was not significant factor that affect the Artificial Intelligence (AI) adoption in supply chain.

There are 2 hypothesis that rejected because the significant of the 2 factor which is organization factor and environment factor are higher than 0.05. So, the researcher concludes that these two factors are not significant to each other.

4.6 Summary

In conclusion, this part provides a thorough assessment of the study findings and analytical techniques. The analyses performed comprised essential categories such as descriptive analysis, reliability analysis, and regression analysis. Each of those methods was critical to gaining useful insights from the data and confirming the study's aims. The descriptive analysis provided a complete summary of the respondents' demographic features, which were clearly displayed in tables and charts for easy interpretation. These graphics improved understanding of the data's structure and assisted in identifying patterns and trends within the questioned population.

The reliability analysis verified that the survey instrument was consistent and reliable, with Cronbach's alpha values verifying the strength of the study's items. The regression analysis, on the other hand, emphasised the relationships between the independent variables technology, organisation, and environment and the dependent variable, the use of Artificial Intelligence (AI) in supply chain. One hypothesis was supported in this study based on statistical significance (p-value < 0.05). This conclusion emphasises the relevance of the elements that influence AI adoption and adds to the study's theoretical framework.

Finally, Chapter 5 delves further into the research's implications and suggestions, as well as a larger discussion of the findings. The following chapter will synthesise the findings, give actionable recommendations, and provide topics for further investigation.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.0 Introduction

This chapter provides a full overview of the conclusions from the data analysis reported in Chapter 4. The researcher will examine the findings and relate them to the research questions and objectives define earlier in the study. This part tries to give a more in-depth explanation of the insights generated from the analysis and how it relates to the research's main objective. The chapter provides with reviewing the research questions to see how well the data collected and analysed addressed them. Similarly, the study objectives will be addressed in depth, emphasising how the findings relate to the investigation's intended purposes. This thoughtful discussion will provide insight on the implications of the findings and their importance in relation to the study's emphasis, specifically the use of Artificial Intelligence (AI) in supply chain.

In addition to analysing the findings, this chapter makes practical recommendations for further study. These recommendations will serve as a guideline for academics and practitioners who want to broaden the scope of this study or explore further into related subjects. The chapter seeks to bridge the gap between existing findings and anticipated improvements in the subject, delivering a well-rounded conclusion to the study.

5.1 Summary of Descriptive

The respondents for this study are mostly from the retail industry, with an emphasis on the use of artificial intelligence (AI) in supply chain management. The demographic study indicated a broad responder profile, with 88 individuals sharing details about their backgrounds. Gender distribution is 55% male, 45% female. This suggests that males outweigh females in retail industry jobs, which may represent gender dynamics within the sector.

The age distribution of responders indicated a greater concentration in the younger groups. The biggest age group was 25-34, with 41 responders. This is most likely due to people in this age group are frequently at the highest level of their careers, taking on responsibilities that need creativity and adaptability, both of which are essential for accepting AI technology. The second biggest group, aged 18-24, accounted for 36.4% of respondents, indicating a high number of younger people joining the retail business. Conversely, the under-18 age group had the lowest representation, with only one respondent, most likely due to limited eligibility for full-time employment. Similarly, just three respondents were beyond the age of 44, indicating that older people may have fewer operational positions in retail, maybe owing to job changes or retirement.

The findings were further strengthened by the ethnic diversity of respondents. Malays made up the majority of the participants (49, 55.7%), mirroring Malaysia's retail workforce demographics. Chinese responses followed, accounting for 30.7%, showing a large presence in retail roles. Indians had 9 respondents, whereas the "Others" group, which included ethnicities such as Kadazandusun and Iban, had just 3 participants, indicating under-representation. This race split reflects the retail sector's variety while also reflecting Malaysia's overall population structure.

Next, the respondents' job descriptions are in retail. CEOs and directors were the least represented, with only two, indicating little participation from top executives, potentially due to time restrictions or delegating of such surveys to subordinates. Managers or supervisors were highly represented, with 23 respondents (26.1%), emphasising their critical role in decision-making and operations. Operational and technical workers accounted for 19.3%, whereas warehouse employees were the most represented category, with 29 responses, highlighting the importance of logistics in retail. The "Others" group comprised 17 responses, suggesting a wide range of jobs that were not precisely classified.

Respondents' years of experience levels varied greatly. The majority (65.9%) had 2-4 years of experience, indicating stability and growth in the field. Those with less than two years of experience represented 19.3% of the sample, demonstrating a consistent infusion of new talent. Workers with 5-7 years of experience made up 11.4%, while just 3.4% had more than 7 years in their present employment. The low proportion of long-tenured employees may indicate opportunities for advancement outside of the retail industry or difficulties in maintaining experienced personnel.

Respondents had unusually high awareness of AI ideas, with 84 (95.5%) reporting acquaintance with them. This underlines the growing importance of AI in retail, where automation and data-driven solutions improve productivity and consumer experiences. Only four respondents (4.5%) were unfamiliar with AI, demonstrating that knowledge gaps in this field are minor.

The adoption of artificial intelligence in respondents' organizations varies. A sizable majority (59 respondents, 67.0%) indicated AI adoption, indicating broad technology integration into retail operations. However, 19 respondents reported that their organisations had not yet implemented AI, maybe owing to financial, technological, or strategic hurdles. Furthermore, 10 respondents were confused about AI adoption in their companies, indicating potential communication gaps or low employee understanding of organisational plans.

These findings provide a comprehensive understanding of the demographic and professional composition of retail industry respondents while highlighting trends and challenges in AI adoption and awareness.

5.2 Discussion Of The Objective

In this part, the researcher outlines the study's objectives in depth, laying the groundwork for understanding the research's direction and purpose. The objectives were defined in response to the stated research challenge and informed by the findings of the literature study. These objectives provide a framework for the researcher to successfully plan the study and coordinate the data collecting and analysis procedures. By identifying precise objectives, the researcher guarantees that the study remains focused and examines the major parts of the research subject in depth. To achieve these goals, a well-structured questionnaire was created that included the important features and characteristics important to the study. The questionnaire was carefully constructed to gather data relevant to the study aims and shared to a representative sample of respondents. This strategy assures that the obtained data is reliable and valid, providing a strong foundation for analysis and conclusions.

5.2.1 Identify the factors that affects the artificial intelligence adoption in supply chain.

The main objective of this research was to determine the variables affecting the supply chain industry's adoption of artificial intelligence (AI). Data from respondents employed by commercial companies was gathered using an effectively questionnaire to accomplish this objective. The questionnaire examined the variables to see how they affected the adoption of AI, including organisational structure, technological readiness, and environmental impacts. The study was able to identify the elements that positively and negatively influenced the adoption of AI technology by examining the replies. Technology readiness, for example, was shown to be crucial in helping AI integration, although environmental conditions and organisational support were less important, possibly as a result of sample variety or industry focus limitations. These results are consistent with earlier study by Oliveira and Martins (2011), who highlighted the significance of technical readiness and infrastructure as significant drivers of technology adoption in organisational settings. The information gained from the questionnaire analysis not only confirmed the importance of certain factors but also highlighted up areas that needed more research. This strategy guarantees that future research may expand on these discoveries to create more thorough frameworks for understanding the adoption of AI in the supply chain sector.

According to the researcher, the independent factors examined in this study have a positive relationship with the supply chain industry's adoption of artificial intelligence (AI), proving its validity. The technological component of these criteria turned out to be the most important in determining the adoption of AI. The most important factor in enabling the adoption of AI is technological preparedness, which includes having access to skilled professionals, compatible systems, and cutting-edge infrastructure. The results show a substantial association between the technological component and the dependent variable, supply chain adoption of AI, with a p-value of less than 0.01. This conclusion is further supported by the coefficient table, which shows that businesses with strong technological skills have an advantage to use AI to optimise supply chain processes. This finding is in alignment with studies by Tornatzky and Fleischer (1990), who found that one of the main factors influencing the acceptance of innovations in organisational settings is technological preparedness. The availability of resources and infrastructure are two technological elements that are essential for a successful technology integration, according to research like those conducted by Baker (2012). These results highlight how crucial technical readiness is to removing obstacles and promoting the successful integration of AI in supply chain management, which should be a priority for both researchers and practitioners.

The organisational factor, which encompasses aspects like organisational structure, society, and resource allocation in the process of implementing artificial intelligence (AI) in the supply chain industry, was the second factor this study looked at. With a coefficient of 0.133 ($p > 0.05$), the questionnaire findings showed that, despite its theoretical significance, this component had no discernible impact on the adoption of AI. There might be a number of causes for this lack of importance. It is possible that many organisations do not have the leadership commitment or mature structure necessary to give AI programs top priority. Ifinedo (2011) points out that organisational preparedness, which includes strategy alignment and leadership support, frequently acts as an obstacle in the adoption of new technologies. AI adoption can also be limited by organisational culture reluctance to change, since management and staff may be hesitant to accept new technology. Another reason may be that, although organisational structure is crucial, external factors or technology preparedness may have a more immediate influence on the use of AI. According to research by Zhu, Kraemer, and Xu (2006), organisational variables that drive technology adoption are frequently overshadowed by external factors such as market dynamics and technological considerations. These results emphasise the need for more study to examine strategies for enhancing organisational preparedness for the use of AI.

This study explored the environmental factor as a possible driver of AI adoption in the supply chain industry. This element includes external effects including market competitiveness, regulatory rules, and consumer desire. With a coefficient of 0.092 ($p > 0.05$), the questionnaire findings, however, showed that this factor was not significant. This suggests that, in the context of the organisations examined, environmental variables had little effect on the adoption of AI. The absence of outside incentives or pressure to use AI in the retail supply chain may be one explanation for this insignificance. For instance, businesses might not be under a lot of pressure from the competition or from laws requiring them to use AI. Although external variables frequently play a significant role in technology adoption, their effects might differ based on industry-specific dynamics, according to Tornatzky and Fleischer's Technology-Organization-Environment (TOE) paradigm (Tornatzky & Fleischer, 1990). Additionally, some organisations may see technical availability or internal readiness as more important than environmental variables. According to research by Oliveira and Martins (2011), when organisations lack the tools or expertise to properly respond to outside possibilities, environmental variables may have less of an impact on technology adoption. These results demonstrate the complexity of environmental factors and the necessity of specialised approaches to remove outside obstacles to the adoption of AI.

In summary, the results show that the only significant factor that helped the study reach its goal of comprehending AI adoption in the supply chain industry was the technological factor. On the other hand, the environment and organisation variables were considered insignificant, most likely as a result of external influences, internal preparation, or resource restrictions.

5.2.2 Analyze the most significant factor that affects the artificial intelligence adoption in supply chain.

The most significant factor influencing the adoption of Artificial Intelligence (AI) in the supply chain is the technology factor. A key factor in enabling the smooth integration of AI into supply chain processes is technological readiness, which includes the availability of cutting-edge tools, infrastructure, and expertise in the field. Companies are better equipped to use AI tools for process optimisation when they have the IT infrastructure they need, such as reliable data management systems, cloud computing capabilities, and IoT-enabled devices. Technology readiness greatly improves a firm's capacity to adopt AI by facilitating real-time data processing and decision-making, according to research by Wamba-Taguimdje et al. (2020). In addition to reducing operational inefficiencies, this preparedness facilitates automation and predictive analytics, both of which are essential components of contemporary supply chain management. The adoption process is further strengthened by the availability of qualified staff to oversee these technologies, guaranteeing the efficient deployment and maintenance of AI systems.

Furthermore, the scalability and flexibility needed for AI adoption in dynamic supply chain systems are also driven by technology reasons. Organisations can make data-driven choices and quickly adjust to changes in the market thanks to advanced technologies like robotic process automation, machine learning, and predictive analytics. This flexibility is especially crucial in a time when global supply networks and consumer demands are growing deeper. Companies that prioritise technology improvements in their supply chains report increased operational efficiency and resilience to disturbances, citing Ivanov et al.'s (2019) research. AI-powered systems, for example, are able to predict supply chain risks and provide the best remedies, guaranteeing continuity and reducing losses. Furthermore, cloud-based technologies make it easier for stakeholders to collaborate across international supply chains by facilitating smooth data exchange and communication. These advantages highlight the importance of technology in gaining competitive advantages in the supply chain industry and make it an essential factor of effective AI deployment.

5.3 Limitation

Several problems occurred throughout the data gathering and analysis phase of this research. One major constraint was the ability to determine the sample population. The researcher decided to focus on retail companies in Malaysia as the target group for the study. To select the population, the researcher used the Glassdoor website, which gives company information such as employee demographics and organisational characteristics. The researcher used Glassdoor to determine the population size of 80, which served as the foundation for the study sample.

To collect data, the researcher designed a questionnaire in Google Forms, assuring accessibility and simplicity of distribution. The questionnaire link was then shared with retail firms to collect replies. However, at the end of the data collecting period, the researcher had obtained 88 replies, slightly more than the initial population estimate. The overlapping may raise issues regarding data quality or representativeness, since some replies may have come from persons outside the intended group or that Glassdoor's population estimate was not entirely thorough.

Despite those challenges, the findings were mostly positive and relevant for the research aims. The replies gave useful information on the study, while the researcher admits the possibility of slight mistakes or errors caused by sampling issues. This constraint emphasises the necessity for future studies to use more precise methodologies for population estimates and sample validation, resulting in even higher accuracy and dependability in comparable research initiatives.

5.4 Recommendation

In this section, the researcher had several suggestions for the future researcher if want to do research about Artificial Intelligence (AI) in supply chain. One of the most essential recommendations for future study on AI deployment in the supply chain is to increase the sample size and diversity. A larger and more diverse sample will result in more reliable and applicable findings. According to Chien and Chen (2011), the impacts of using AI in supply chains different based on the organization's size, industry, and location. Large organisations, for example, may have greater resources to invest in AI technology, but smaller enterprises may have financial or technological limits. Expanding the sample size to include organisations from diverse sectors, such as retail, manufacturing, and logistics, could help in identifying industry-specific obstacles and opportunities when using AI. Furthermore, integrating organisations from various geographical locations would shed light on how AI use varies across established and emerging countries. For example, AI adoption in wealthier nations may be more advanced owing to improved infrastructure, but underdeveloped countries may face various challenges. Future study should include a wider variety of organisations to better understand AI's broader influence across various business contexts.

Another important suggestion is to investigate the obstacles to supply networks' use of AI. Financial limitations, a lack of technical knowledge, and opposition to change are major barriers to AI adoption in many organisations, according to research by Avasarala and Yadav (2020). Even though AI has many obvious advantages, such increased productivity and lower costs, organisations frequently encounter obstacles that prevent complete adoption. According to research conducted in the industrial industry by Chui et al. (2018), many businesses find it difficult to incorporate AI because of outdated legacy systems, a shortage of experienced labour, or staff concerns about losing their jobs. Examining these challenges will give future students important information about the particular difficulties companies encounter and help in the creation of workable solutions. For companies thinking about implementing AI but unclear of how to move forward, finding answers to these obstacles might be revolutionary. Understanding these obstacles would also allow governments to provide resources and advice to businesses seeking to successfully incorporate AI into their supply chains.

For AI to be successfully integrated, organisational and technological barriers must be addressed. According to Westerman et al. (2014)'s research on digital transformation, businesses frequently encounter internal opposition from staff members who worry that AI will replace them or interfere with current workflows. Leadership and organisational culture have a big impact on how AI is used and embraced. According to research by Brynjolfsson and McAfee (2014), businesses that consistently invest in employee upskilling and foster an innovative culture have a higher chance of success when implementing AI. Future studies can help companies overcome cultural barriers and align their personnel with AI integration by examining these internal difficulties. Furthermore, for AI adoption to be effective, it is essential to understand the technological challenges, such as data security issues and interface with previous systems. By removing these obstacles, companies would be better equipped to decide whether to use AI and make the changes more seamless, which would eventually result in supply chain operations that are more competitive and efficient.

5.5 Conclusion

The adoption of artificial intelligence (AI) in the supply chain industry, namely in retail businesses, was the main emphasis of this study. The goal of the study was to investigate a number of variables that may affect the implementation of AI technology. The adoption of AI in the supply chain was shown to be unaffected by two important criteria in the previous chapter: environment and organisation. As was said in the previous section, this result could be explained by several restrictions in the research design. To adequately capture the impact of these factors, for example, the sample size may not have been sufficiently broad or varied. Furthermore, the study was restricted to retail companies, which could not have accurately reflected the broader range of sectors implementing AI in their supply chains.

Reliability analysis, regression analysis were among the analytical techniques used to guarantee the validity and dependability of the data gathered. These methods assisted in evaluating the degree of correlation between the variables and identifying the importance of the factors in affecting the adoption of AI. The data collection questionnaire was thoughtfully crafted to gather a wide range of respondents' viewpoints about the adoption of AI. It contained enquiries about environmental conditions, organisational structure, and technical preparedness, all of which were examined for trends and connections.

Even though the organisation and environment factors did not significantly affect this study, it is crucial that future research explore these areas further with a more varied sample and possibly broaden the scope to include other industries, like manufacturing and logistics to get a more comprehensive picture of supply chain AI adoption trends.

CONCLUSION

The study aimed to investigate factors influencing Artificial Intelligence (AI) adoption in the supply chain industry, focusing on retail businesses. Using robust methodologies, such as reliability analysis and regression analysis, the research evaluated the relationships between technological readiness, organizational factors, and environmental influences. Among these, technological readiness emerged as the most significant factor affecting AI adoption. Access to advanced tools, infrastructure, and skilled professionals proved crucial for integrating AI effectively into supply chain operations. This finding underscores the importance of technological preparedness as a foundation for successful AI implementation.

Conversely, organizational and environmental factors were not found to significantly influence AI adoption in this study. Organizational readiness, such as leadership commitment and cultural adaptability, may have been underrepresented due to sample limitations or the specific focus on retail businesses. Similarly, environmental factors like market competition and regulatory pressures might not have been strongly felt in the surveyed organizations. These results suggest that while technological readiness is critical, other factors require further exploration to understand their potential impact on AI adoption comprehensively. Additionally, the insignificance of these factors may be attributed to their status as standard practices in companies adopting AI. Organizations naturally establish supportive internal practices and respond to external market demands as part of routine operations when integrating AI technologies. Therefore, these factors may not stand out as strong differentiators but rather as necessary and expected practices embedded in modern AI-driven operations. Understanding how such practices evolve and become routine may shed light on more nuanced enablers of AI adoption in future research.

The study's methodology, including structured questionnaires and Exploratory Factor Analysis (EFA) using SPSS version 29, ensured data reliability and validity. However, limitations, such as a restricted sample size and industry focus, may have influenced the findings. Future research should address these gaps by including diverse industries and broader geographic representation to capture a holistic view of AI adoption trends.

In conclusion, the study highlights the central role of technology in driving AI adoption in the supply chain, while also identifying areas for further research. These insights provide a foundation for businesses and policymakers to prioritize technological advancements and explore strategies to enhance organizational and environmental readiness for AI integration.

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APPENDIX

APPENDIX A:

QUESTIONNAIRE QUESTION FOR ANALYZE FACTOR THAT AFFECT THE ARTIFICIAL INTELLIGENCE (AI) ADOPTION IN SUPPLY CHAIN.

SECTION A - DEMOGRAPHIC PROFILE

In this section, there are listed a few related questions with your profile. Please tick (√) in the prepared box if the answer right.

1) Gender

a.	Male	
b.	Female	

2) Age

a.	Under 18	
b.	18-24	
c.	25-34	
d.	35-44	
e.	Above 44	

3) Race

a.	Malay	
b.	Chinese	
c.	Indian	
d.	Others	

4) Job Category

a.	CEO/Director	
b.	Manager/ Supervisor	
c.	Operation/ Technical	
d.	Warehouse Staff	
e.	Others	

5) Years at Current Role

a.	0 – 1 years	
b.	2 – 4 years	
c.	5 – 7 years	
d.	> 7 years	

6) Do you know about Artificial Intelligence (AI)?

a.	Yes	
b.	No	

7) Did your workplace or industry that you work now implement AI?

a.	Yes	
b.	No	
c.	Not sure	

SECTION B – FACTORS THAT AFFECT THE ADOPTION OF ARTIFICIAL INTELLIGENCE (AI) IN SUPPLY CHAIN

In this section, there are the factors that affect the adoption of artificial intelligence (AI) in supply chain, please tick (√) in the following statement by using appropriate scale below:

1: Strongly Agree 2: Agree 3: Neutral 4: Disagree 5: Strongly Disagree

1) Technology

No.	Question	1	2	3	4	5
1.	The company's IT infrastructure is capable of supporting AI.					
2.	The technologies used by our suppliers will be compatible with AI					
3.	The technologies used by our customers will be compatible with AI.					
4.	The company's unit has the necessary skills to support AI initiatives.					
5.	The company's unit is committed to ensuring that employees are trained in AI.					
6.	The organization has a high degree of AI expertise.					

2) Organization

No.	Question	1	2	3	4	5
1.	Top management in our company unit are likely to invest funds in AI.					
2.	Top management in our company unit is willing to take risks involved in the adoption of AI.					

3.	Top management in our company unit is likely to consider the adoption of AI to gain a competitive edge.					
4.	AI technologies have high setup costs.					
5.	AI technologies have high running costs.					
6.	AI technologies have high maintenance costs.					

3) Environment

No.	Question	1	2	3	4	5
1.	The regulations and policies will hold back the adoption of AI in the company unit.					
2.	The current business laws and regulation support AI operations and adoption in the company unit					
3.	The government provides support for AI technology adoption					
4.	The company would be under pressure from competitors to adopt AI.					
5.	The company's competitors are adopting AI.					
6.	The company will have a competitive disadvantage if not embracing AI.					

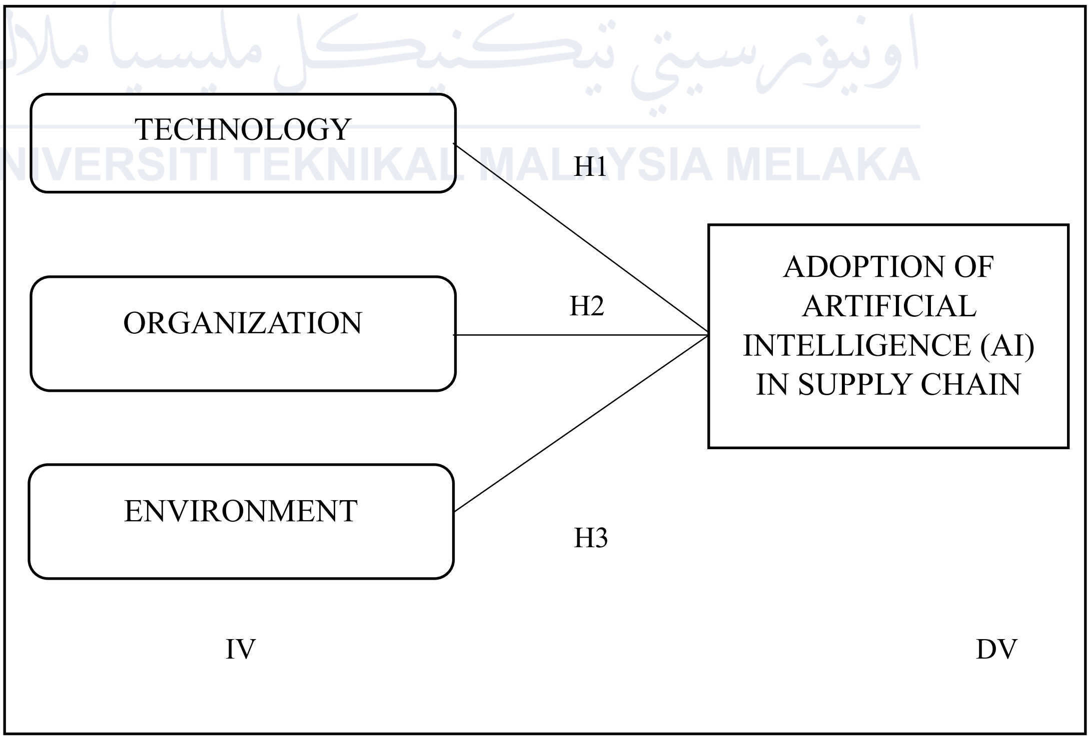
SECTION C - DEPENDENT VARIABLE (DV) - ADOPTION OF ARTIFICIAL INTELLIGENCE (AI) IN SUPPLY CHAIN

No.	Question	1	2	3	4	5
1.	I find it easy to use artificial intelligence (AI) tools in the supply chain process.					

2.	Learning to operate AI-based applications in supply chain management is straightforward.					
3.	I am confident in my ability to use AI technologies to support supply chain tasks.					
4.	AI adoption has improved the efficiency of supply chain operations					
5.	AI tools in supply chain management help to reduce operational costs.					
6.	Using AI in the supply chain helps us make better, data-driven decisions.					

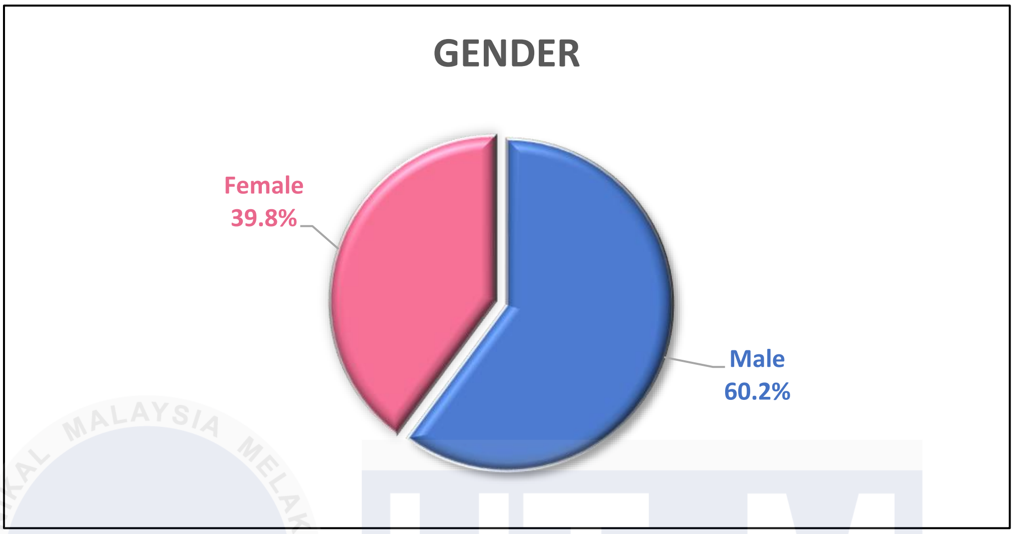
APPENDIX B:

THEORITICAL FRAMEWORK



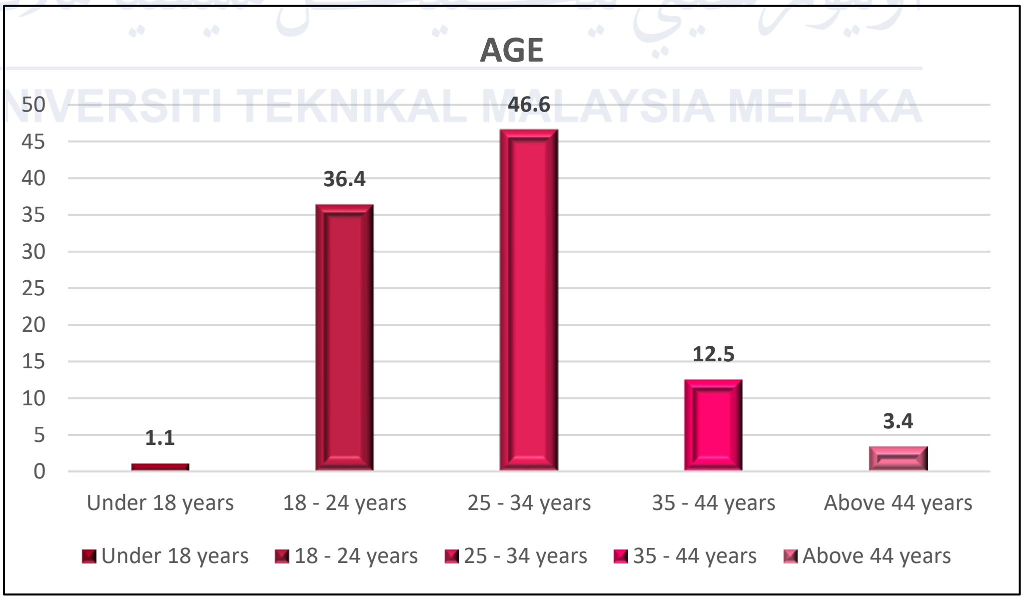
APPENDIX C:

RESPONDENT'S GENDER



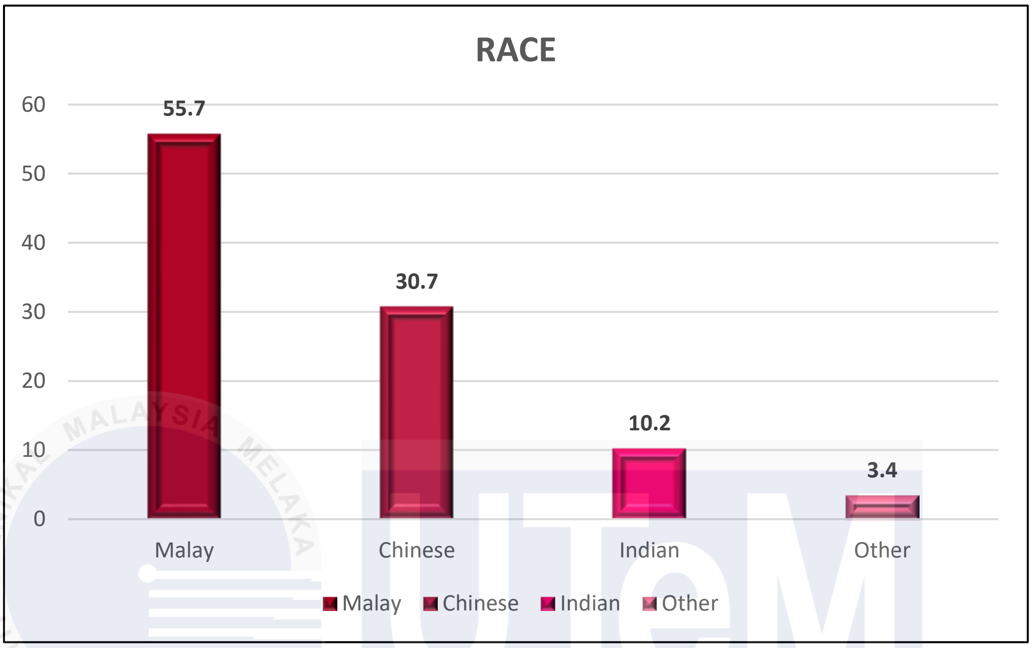
APPENDIX D:

RESPONDENT'S AGE



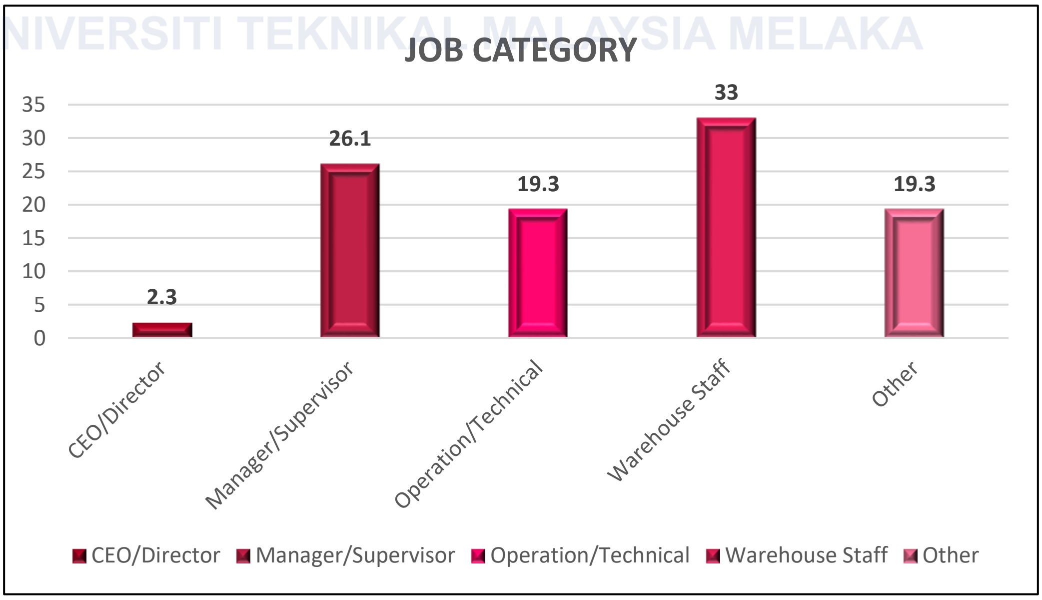
APPENDIX E:

RESPONDENT'S RACE



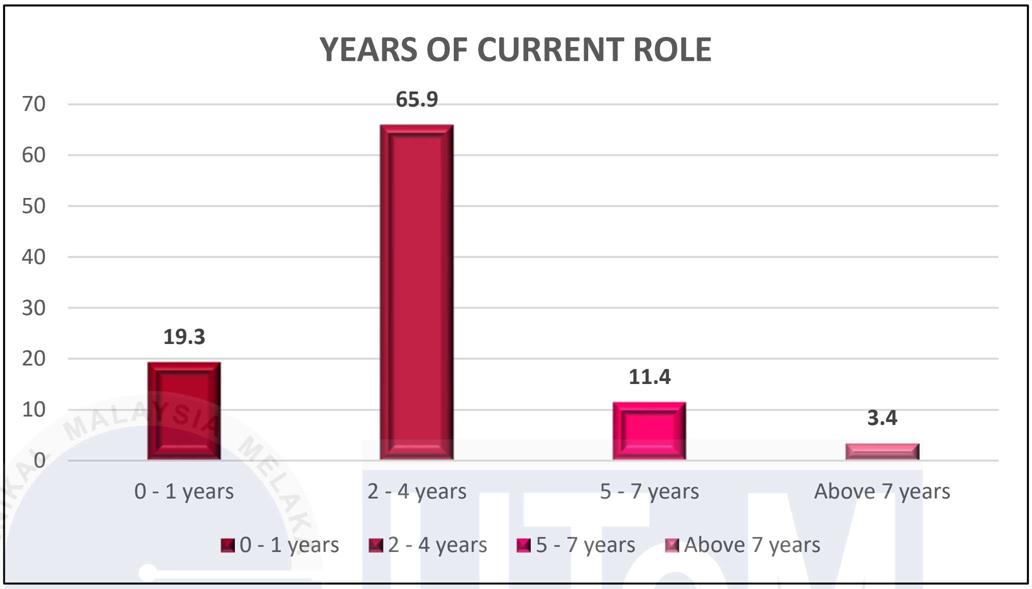
APPENDIX F:

RESPONDENT'S JOB CATEGORY



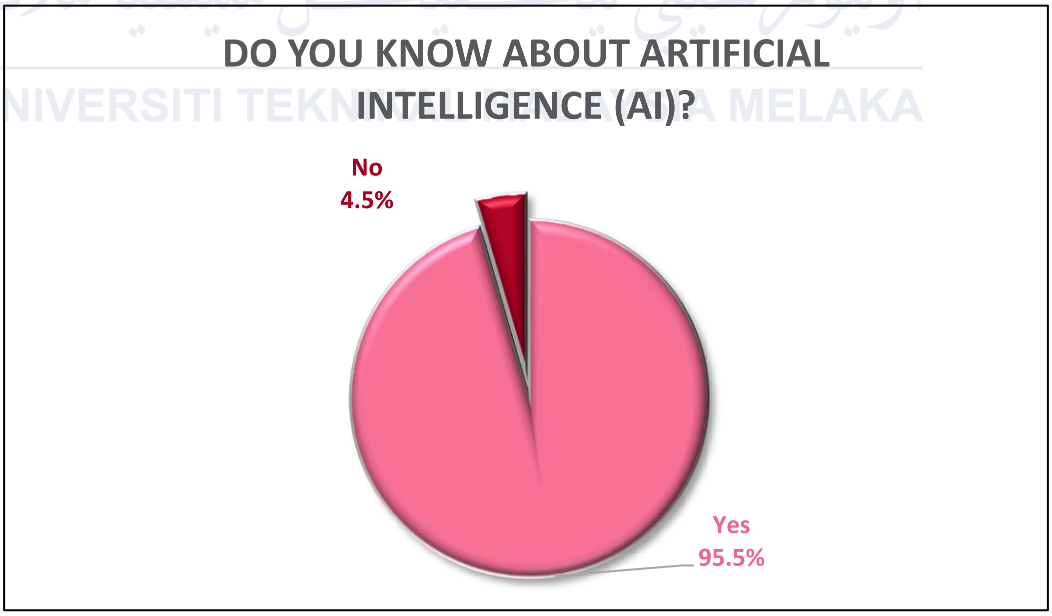
APPENDIX G:

RESPONDENT'S YEARS OF CURRENT ROLE



APPENDIX H:

RESPONDENT'S AWARENESS ABOUT ARTIFICIAL INTELLIGENCEE



APPENDIX I:

DID RESPONDENT'S WORKPLACE IMPLEMENT ARTIFICIAL INTELLIGENCE?