EVALUATING DRIVERS OF ARTIFICIAL INTELLIGENCE ADOPTION ON INVESTMENT DECISION-MAKING IN MALAYSIA'S FINANCIAL MARKET

AGNES WONG ONN YEE

SAW KER XUEN

YEE JIA HUI

BACHELOR OF BUSINESS ADMINISTRATION (HONOURS) BANKING AND FINANCE

UNIVERSITI TUNKU ABDUL RAHMAN

TEH HONG PIOW FACULTY OF BUSINESS AND FINANCE

DEPARTMENT OF BANKING AND RISK MANAGEMENT

APRIL 2026

WONG, SAW, & YEE	AI IN FINANCIAL MARKET	BBF (HONS)	APRIL 2026

EVALUATING DRIVERS OF ARTIFICIAL INTELLIGENCE ADOPTION ON INVESTMENT DECISION-MAKING IN MALAYSIA'S FINANCIAL MARKET

BY

AGNES WONG ONN YEE

SAW KER XUEN

YEE JIA HUI

A final year project submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF BUSINESS ADMINISTRATION (HONOURS) BANKING AND FINANCE

UNIVERSITI TUNKU ABDUL RAHMAN

TEH HONG PIOW FACULTY OF BUSINESS AND FINANCE

DEPARTMENT OF BANKING AND RISK MANAGEMENT

APRIL 2026

DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work, and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

(4) The word count of this research report is 18,706.

Name of Student:	Student ID	Signature
1. Agnes Wong Onn Yee	2104203	
2. Saw Ker Xuen	2202697	
3. Yee Jia Hui	2104205	

Date: 22/04/2026

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to everyone who has contributed to the successful completion of this Final Year Project entitled "Evaluating Drivers of Artificial Intelligence Adoption on Investment Decision-Making in Malaysia's Financial Markey".

First and foremost, we would like to convey our deepest appreciation to our supervisor, Dr. William Choo Keng Soon, for the continuous guidance, valuable advice, constructive feedback, and encouragement throughout the entire research process. His patience and support has been instrumental in helping us complete this study successfully.

We would also like to express our sincere appreciation to Universiti Tunku Abdul Rahman (UTAR) for providing us with the opportunity, resources, and supportive learning environment to carry out and complete this research project.

In addition, we would like to thank all respondents who willing participated in our survey and provided valuable information for this study. Without their cooperation, this research would not have been possible.

Lastly, we would like to thank everyone who has directly or indirectly contributed to the completion of this research project. Your support and assistance are greatly appreciated.

PREFACE

The rapid development of Artificial intelligence (AI) has significantly transformed the financial industry, particularly in investment decision-making, risk management, and trading systems. As Banking and Finance students, we developed an interest in understanding how AI influences financial market activities in Malaysia, which motivated us to explore the factors driving its adoption in financial market decision-making.

This study was conducted to examine the relationship between several factors, including market efficiency and accuracy, human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, investor perception and trust, and the intention to adopt AI in Malaysia's financial market. The topic was chosen due to the growing importance of AI in shaping modern investment practices, as well as the limited empirical evidence available in Malaysia.

Throughout this research process, we gained valuable experience in academic research, from data collection to statistical analysis and interpretation, while applying theoretical knowledge to a real-world finance issue.

We hope this study provides useful insights for future researchers, policymakers, and financial professionals in understanding AI adoption in the financial market.

ABSTRACT

This study investigates the drivers of Artificial Intelligence (AI) adoption and their impact on investment decision-making in Malaysia's financial market. The study examines the relationship between enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, investor perception and trust, and the intention to adopt AI in the financial market decision-making. A quantitative research design was employed, and primary data were collected through structured questionnaires distributed to Malaysian investors aged 18 and above who have experience with AI-enabled financial tools such as robo-advisors and algorithmic trading platforms. The collected data were analyzed using descriptive analysis, reliability testing, Pearson correlation, and multiple linear regression analysis. The findings show enhanced market efficiency and accuracy, reduction in human bias, and personalized investment strategies have a positive significant relationship with the intention to adopt AI in the financial market decision-making. In contrast, ethical and regulatory challenges, market adaptation and technological barriers, investor perception and trust have a negative significant relationship with the intention to adopt AI in the financial market decision-making. These findings provide useful insights for policymakers, financial institutions, and future researchers in promoting effective AI adoption in Malaysia's financial market.

Keyword: Artificial Intelligence (AI), Investment, Financial Market, Diffusion of Innovations Theory, Malaysia

Subject Area: HG450- 6051 Investment, Capital Formation, Speculation

TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
AI	Artificial Intelligence
AI	Intention to Adopt AI in Malaysia's Financial Market Decision-Making
BNM	Bank Negara Malaysia
DFIs	Development Financial Institutions
DL	Deep learning
DoI	Diffusion of Innovation Theory
ERC	Ethical and Regulatory Challenges
e-KYC	e- Know Your Customer
EMEA	Enhanced Market Efficiency and Accuracy
EMH	Efficient Market Hypothesis
GDPR	General Data Protection Regulation
HFT	High-Frequency Trading
IPT	Investor Perception and Trust
KPI	Key Performance Indicator
LLMs	Large Language Models
MATB	Market Adaptation and Technological Barriers
MLR	Multiple Linear Regression
ML	Machine Learning
NLP	Natural Language Processing
PIS	Personalized Investment Strategies
RHB	Reduction in Human Bias
ROI	Return on Investment

RMiT	Risk Management in Technology
SPSS	Statistical Package for the Social Sciences
SVM	Support Vector Machines
UTAR	Universiti Tunku Abdul Rahman
VIF	Variance Inflation Factor
XAI	Explainable AI

LIST OF APPENDICES

Page

CHAPTER 1: INTRODUCTION

1.0 Introduction

This chapter begins with the research background, then followed by problem statement, which discusses the issue related to the study being investigated. Moreover, the research objectives and questions are presented to serve as a guide for this study. Finally, the significance of study discussed the contribution of this study to advancing knowledge in the field.

1.1 Research Background

1.1.1 Malaysian Financial Markets

Financial market in Malaysia is an important part of the Malaysian financial system, which works together with financial institutions to promote capital allocation, management of liquidity, and economic stability. It includes different markets like the money and foreign exchange markets, capital market, and the derivatives market which are regulated by authorities, among them, Bank Negara Malaysia (BNM) and the Securities Commission (SC) Malaysia (BNM, 2006). According to CEIC (2025), the market capitalization of Malaysia stock market stood at US$406 billion in Feb 2025. These markets have also changed over the years in terms of structure as they have moved away towards digitalized platforms, in line with the global financial innovation and technological advancement. The market is usually divided into money market, foreign exchange market, capital market and the derivatives market, each of them having a unique role in ensuring financial stability and growth (Bank Negara Malaysia, 2023).

The introduction of high technologies into the financial markets is not something new. The 1990s witnessed the emergence of electronic trading platforms all over the world, whereas the early 2000s introduced the online banks, mobile transactions, and automated systems (Ranjan, 2024). In Malaysia, the same trends were observed as Bursa Malaysia was introduced to electronic trading and online financial services, which were promoted by the government through strategies to increase digital competitiveness (Bursa, 2025).

On the other hand, money market in Malaysia is mainly the place where short-term borrowing and lending takes place which is the source of liquidity to the financial institutions and corporations. Closely associated with this is the foreign exchange market which is a necessity in international trade and investment since it is the mechanism through which currencies are exchanged. Malaysia has a trade-based economy that is highly dependent on the smooth operation of the foreign exchange market to control the exchange rate volatility and capital flows (Bank of International Settlement, 2022). The capital market, in contrast, offers long-term funding in the form of equity and debt instruments and Bursa Malaysia serves as the main marketplace to trade shares and bonds. Malaysia is also known to have a dynamic Islamic capital market, with Malaysia remains as the biggest global sukuk market with a share of 52% of total sukuk outstanding and 42% share of global sukuk (BNM, 2023).

The financial markets in Malaysia have evolved tremendously over the decades, with the introduction of new trading systems, the embrace of electronic trading systems, and the implementation of new regulatory frameworks that enhance transparency and efficiency of the markets. The industry has proven to be resilient and has been able to adapt to global financial crises and domestic reforms and is progressing steadily towards digitalization. The development of these subsectors reflects the increasing complexity and entanglement of the financial system and thus the necessity of constant innovation.

1.1.2 AI in the Financial Market

Artificial Intelligence (AI) has become a key driver of digital transformation across industries. According to Milana and Ashta (2021), private equity firms are increasingly accelerating the digital transformation of analogue enterprises by adopting technologies such as AI and data analytics. This trend is not merely about replacing human labour with machines, but about uncovering customer needs and improving service delivery. A similar trend of adopting AI can also be observed in the financial sector, where AI has rapidly expanded in recent years. Financial institutions increasingly leverage AI for risk management, credit scoring, personalized investment advice, and customer support. Besides the private sector, financial authorities such as central banks are also exploring the potential use of AI in order to improve economic forecasting, analysis, and monitoring (Bai et al., 2024).

Furthermore, AI's evolution in the financial market has been evolutionary. According to Aldasoro et al. (2024), the early AI in the financial market only relied on rule-based systems, such as "if-then" logic, to automate basic analytical tasks like fraud detection and risk assessment. Then, the introduction of Machine Learning (ML) in the 2010s enabled more complex data-driven applications in areas such as credit scoring and algorithmic trading. Furthermore, Large Language Models (LLMs) and generative AI are added in today's phase. These tools allowed tasks like information extraction from news, chats, and files. Also, LLMs can be used for back-end processing, robo-advising, fraud detection, and so on in the financial sector. This evolution demonstrates how AI has moved from being a simple automation tool to becoming a central, transformative force in shaping the modern financial sector.

The current stage of AI integration into the financial market shows both opportunities and challenges. On the opportunity side, AI improves credit assessment and investment decisions by processing the large amounts of data generated by financial institutions. This allows to have a more accurate, faster, and informed decision-making process (Maple et al., 2023). Additionally, AI-based models can effectively support the achievement of ESG investment targets (Ashta and Herrmann, 2021) and recommend the investment portfolio construction and reconstruction (Ahmed et al., 2021). Moreover, algorithmic trading has proven to be more efficient than human traders because it uses real-time data to quickly detect market anomalies and adjust for the price differences. Al-models can also detect unexpected market trends within a limited time, which allows them to send better trading signals to human traders. Thus, AI models can be more efficient compared to human traders (Maple et al., 2023).

However, these advancements also introduce challenges that require careful consideration. According to Fletcher & Le (2021), the key concern of using AI in the financial market is the lack of transparency, which is often referred to as the "black box problem". A black box refers to a challenge that humans face while trying to understand or explain how AI generates its results. In this case, users are unable to understand how the system functions or how decisions are made, and the underlying reasons behind those decisions. This creates a challenge in identifying biases and errors in the system, which may further lead to inaccurate and unfair decisions (Maple et al., 2023).

In conclusion, AI is important in the financial market as it can enhance decision-making, optimize operations, and drive innovation across the sector. At the same time, it also raises challenges, especially the issue of transparency in decision-making processes. Therefore, financial institutions and regulators must work together to enhance transparency in order to ensure AI can bring a positive impact to the financial markets in the long run.

1.1.3 AI in Malaysia Financial Market

Artificial Intelligence (AI) is transforming Malaysia's financial market by enabling smarter, more efficient, and inclusive financial services. Financial institutions are increasingly adopting AI in customer analytics, fraud detection, e-Know Your Customer (e-KYC), and operational automation. A recent survey by Bank Negara Malaysia (BNM) reported that 71% of banking institutions and development financial institutions (DFIs) have deployed at least one AI application ("Artificial Intelligence in the Malaysian Financial Sector," 2025). On the regulatory side, BNM has introduced a discussion paper on AI governance, emphasizing fairness, ethics, accountability, and transparency while leveraging existing frameworks such as Risk Management in Technology (RMiT) (Hong, 2025).

The adoption of AI is driven by Malaysia's broader digital transformation agenda, which position Malaysia as a regional digital hub (Rowena, 2025). According to BNM and industry surveys, over 80% of banks have initiated AI-driven projects, particularly in fraud detection and customer service automation (Zahid, 2024). In addition, AI contributes to financial inclusion, with alternative credit scoring models expanding access to financing for underserved communities (Sam-Bulya et al., 2021). In Islamic finance, AI supports Shariah compliance automation, robo-advisory services, and halal investment screening, aligning Malaysia's dual banking system with technological innovation (Ashurov & Azman, 2025).

Since 2019, spurred by the COVID-19 pandemic and rising digital demand, AI adoption has accelerated significantly. The pandemic acted as a catalyst, forcing banks to strengthen their digital infrastructure and implement AI-driven solutions to ensure business continuity (*Newly Announced Digital Banks to Benefit From Pandemic-driven Digitalisation; Immediate Threat to Traditional Banks Moderated by Regulatory Threshold*, 2022). According to Nor (2024), the adoption of machine learning (ML), deep learning (DL), and Generative AI expanded rapidly in Malaysian banking, especially in fraud monitoring, credit risk modelling, and customer service. In parallel, BNM introduced its Policy Document on Licensing Framework for Digital Banks, under which five licenses were granted in 2022, requiring applicants to embed AI and data-driven capabilities into their business models, for both conventional and Islamic banking business (EY, 2021).

Recent years have seen significant infrastructure investments to support Malaysia's AI-financial ecosystem. For example, Oracle committed more than USD 6.5 billion to establish a public cloud region in Malaysia, enabling banks to modernize applications, migrate workload to the cloud, and innovate with AI-driven analytics (Azhar, 2024). Besides, Microsoft is investing USD 2.2 billion to build cloud and AI infrastructure establish a national AI center, and train more than 300,000 Malaysians (Source, 2024). Together, these initiatives highlight Malaysia's commitment to digital transformation, positioning the nation as a regional leader in AI-powered financial services and sustainable economic growth.

1.2 Problem Statement

Despite the rapid adoption of AI in the global financial market, there is still insufficient evidence to explain its influence on financial market decision-making within the Malaysian context. Firstly, most of the existing literature emphasizes the foreign financial market, but their findings cannot be directly generalized to Malaysia due to the differences in regulatory frameworks, market structures, investor behavior, and trust factors compared to foreign financial markets.

Besides that, the global research shows that factors such as enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust will significantly shape AI adoption in the financial market (Shaikh et al., 2025). However, there is still a lack of evidence that these six factors can influence the intention to adopt AI in Malaysia's financial market.

AI is widely recognized for enhancing market efficiency and accuracy, however, there are still several studies highlighting the limitations that could reduce its effectiveness in financial market decision-making. Limitations such as algorithmic bias, inaccuracies in sentiment analysis, increased market volatility, and high-frequency trading (HFT) manipulation have increased the concern about whether AI can truly improve market efficiency (Yacoub et al., 2024; Nahar et al., 2024). In this case, these limitations create uncertainty for investors due to the reliability of AI-driven insights, which further decreases the intention to adopt AI in Malaysia's financial market.

Moreover, there are concerns about the presence of bias in AI itself, despite the widespread agreement that AI reduces human bias and emotional decision-making in the financial market. This is because AI relies heavily on human-generated data and algorithm design, which may contain conscious or unconscious biases. When the data used to train AI reflects human bias, this bias may be learned and reproduced by the AI. As a result, human bias can influence how AI make decisions in the financial market. This concern may discourage investors from adopting AI in the financial market. However, there is still limited evidence on whether the reduction of human bias influences the intention to adopt AI in Malaysia's financial market.

Although prior studies demonstrate the benefits of AI-driven personalized investment strategies in improving decision-making and investors' satisfaction, there is still limited evidence on whether these benefits influence investors' intention to adopt AI in the financial market. These personalized strategies are expected to improve decision-making performance, increase investors' confidence, and enhance satisfaction with the investment outcome. However, not every investor would consider AI-generated recommendations reliable or useful, especially when they are adjusted over time to match their changing financial needs. Therefore, it remains uncertain whether personalized investment strategies will significantly influence investors' intention to adopt AI in Malaysia's financial market.

Furthermore, ethical and regulatory challenges represent a critical concern in the adoption of AI in the financial market. This is because the concerns about data privacy, transparency, accountability, and fairness will increase when AI is used in financial decision-making. Investors may be worried about how their information is collected, stored, and used because AI systems rely on a large amount of private and sensitive data. Also, investors may become more concerned and perceive risks due to the lack of clear regulatory frameworks and governance standards for AI applications in the finance industry. Moreover, ethical concerns such as algorithmic bias and lack of explainability could further lead investors to reduce their trust in adopting AI in the financial market. In particular, the "black box" nature of many AI systems makes it challenging for investors to understand how decisions are generated. Consequently, these concerns may discourage investors from adopting AI in the financial market. However, there is still lack of empirical evidence on whether ethical and regulatory concerns influence the intention to adopt AI in Malaysia's financial market.

In addition, market adaptation and technological barriers can prevent the widespread adoption of AI in the financial market. In order to integrate AI technologies with current financial systems, a significant financial investment in advanced infrastructure and technical expertise is needed. However, investors may find it challenging to adapt to new technologies due to limited financial resources, low digital readiness, and resistance to technological change. These barriers may slow down the adoption of AI in the financial market despite the potential benefits that AI will bring to investors. However, there is still require further investigation on how market adaptation and technological barriers influence the intention to adopt AI in Malaysia's financial market.

Moreover, investor perception and trust are fundamental factors of AI adoption in the financial market. Many investors may still perceive AI systems as risky, unreliable, or difficult to use, despite the fact that they are intended to improve automation and investment decision-making. In this case, negative perception regarding system accuracy, transparency, and data security will reduce the trust in using AI in the financial market. Since investment decisions involve financial risk, trust becomes a key factor in whether investors are willing to rely on AI. However, there is still insufficient empirical evidence on how investor perception and trust influence the intention to adopt AI in Malaysia's financial market.

Furthermore, most of the existing studies on AI in the financial market remain either conceptual or limited to only one dimension, such as market efficiency or regulatory challenges. However, social factors such as investor perception and trust have received less attention, despite their importance in influencing AI adoption in the financial market (Cao et al., 2025). Hence, there is insufficient empirical validation of social factors within the Malaysian context, which further leads to a theoretical gap in understanding how AI adoption in the financial market is influenced by both technological and social factors.

Without addressing these gaps, the adoption of AI in the Malaysian financial market may face resistance. Regulators and policymakers may struggle to develop governance frameworks, which further increases investors' hesitation to adopt AI in the financial market. Therefore, this study seeks to examine these six factors on the intention to adopt AI in Malaysia's financial market. In this way, this study can provide evidence-based insights that guide Malaysia's policymakers, regulators, and investors in ensuring a more effective and trustworthy in adopting AI in the financial market.

1.3 Research Objectives

a) To examine the relationship between enhanced market efficiency and accuracy and intention to adopt AI in Malaysia's financial market decision-making.

b) To examine the relationship between reduction in human bias and intention to adopt AI in Malaysia's financial market decision-making.

c) To examine the relationship between personalized investment strategies and intention to adopt AI in Malaysia's financial market decision-making.

d) To examine the relationship between ethical and regulatory challenges and intention to adopt AI in Malaysia's financial market decision-making.

e) To examine the relationship between market adaptation and technological barriers and intention to adopt AI in Malaysia's financial market decision-making.

f) To examine the relationship between investor perception and trust and intention to adopt AI in Malaysia's financial market decision-making.

1.4 Research Questions

a) Does the intention to adopt AI in Malaysia's financial market decision-making significantly influenced by enhanced market efficiency and accuracy?

b) Does the intention to adopt AI in Malaysia's financial market decision-making significantly influenced by reduction in human bias?

c) Does the intention to adopt AI in Malaysia's financial market decision-making significantly influenced by personalized investment strategies?

d) Does the intention to adopt AI in Malaysia's financial market decision-making significantly influenced by ethical and regulatory challenges?

e) Does the intention to adopt AI in Malaysia's financial market decision-making significantly influenced by market adaptation and technological barriers?

f) Does the intention to adopt AI in Malaysia's financial market decision-making significantly influenced by investor perception and trust?

1.5 Significance of the Study

Firstly, one of the strengths of this study is that it will facilitate easier study for future researchers on the application of Artificial Intelligence (AI) to financial market decision-making. Future researchers can utilize the findings of this study as a starting point to enhance their own study or reporting. This study also provides researchers with insights and data to guide future research on the ways on how AI influences market efficiency, investor trust, and regulatory matters. In addition, by outlining suggestions, the data about the relationship between market variables, investor attitude, and the application of AI could serve as a benchmark for further similar studies.

Besides, the goal of this study is to give policymakers and finance professionals useful information so they may further utilize AI in the banking sector. Banks and other financial institutions can adjust their business models based on this study's findings and develop strategies for incorporating AI in trading, risk management, and advisory services optimally. Ethical and regulative matters discussed in this study also provide policymakers with greater guidance so that they can apply AI in a responsible way. Therefore, institutions can gain significant advantages if they can adopt AI while being transparent, equitable, and accountable.

Lastly, the contributions of this research are also meant to help financial markets to function more optimally and efficiently through identifying opportunities and challenges of AI deployment. The management of financial institutions can rearrange planning, improve governance frameworks, and strategically redistribute resources to attain the highest profitability and competitiveness. Thus, this study can help stakeholders in identifying potential risks and limitations before they cause negative effects on market operations, investor confidence, or institution reputation in the financial market.

1.6 Summary

To summary, this chapter studied the background of AI in the financial market and outlined the problem statement of this paper. The research objectives and questions were also provided in this chapter. The relationship between the dependent and independent variables will be covered in more detail in the subsequent chapters.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Firstly, literature review will be done to examine the relationship between the independent variables, namely enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaption and technological barriers, investors perception and trust, and the dependent variable, which is AI in financial market decision making. Secondly, theoretical frameworks will be presented to understand the dynamics of these relationships. Next, the conceptual framework will be developed based on the reviewed literature and theories. Lastly, hypothesis development is going to carry out to explore the proposed relationships.

2.1 Review of Literature

2.1.1 AI in Financial Market Decision-Making

Artificial Intelligence (AI) has emerged as a gamechanger in financial markets, transforming traditional processes such as high-frequency trading, fraud detection, risk management, and portfolio optimization (Chakrabarty et al., 2017). As a fast-growing technology, AI is now widely adopted in finance, which helps investors to make smart decisions by quickly analyzing huge amounts of data, commonly known as "Big Data" (Owolabi et al., 2024). Unlike traditional trading, which relies heavily on manual or semi-automated processes, human expertise, and intuition, resulting in restricted data capacity and slower responses (Chakrabarty et al., 2017). Hence, interest in AI-driven techniques has grown due to these inadequacies and the growing complexity of global marketplaces (Shaikh et al., 2025).

The shift toward AI-driven techniques has allowed investors to act faster and accurately (Owolabi et al., 2024). This is important because financial markets generate an enormous amount of data every second, due to high-frequency trading, global transactions, and increasingly interconnected economies. This "Big Data" includes everything from market prices and trading volumes to news reports, financial statements, and social media posts. Given the rapid pace and complexity of this data, human analysts and investors often struggle to extract meaningful insights efficiently (Pillai, 2023). As a result, AI's ability to process and interpret large and diverse datasets in real time is extremely important in modern finance, addressing both the inefficiencies of traditional methods and the growing demands of the global market (Shaikh et al., 2025).

Understanding AI's role in financial decision-making is essential to exploring the underlying technologies, such as Natural Language Processing (NLP), Machine Learning (ML), and deep learning (Pillai, 2023). NLP techniques, for instance, are applied to analyze unstructured text data, such as earnings reports, news articles, and social media posts. Sentiment analysis, which is a part of NLP, helps to understand market feelings by identifying opinions and emotions in financial texts, which allows investors to make better decisions during market ups and downs. Besides that, ML such as Support Vector Machines (SVM), deep neural networks, and decision trees are widely used for predicting stock prices, risk management, and market trends. Lastly, deep learning is a subset of machine learning that is particularly effective for tasks that involve complex data patterns, such as analyzing historical stock trends, assessing credit scores, and supporting high-frequency trading. The combination of these technologies gets to enhance decision-making in the financial market by improving predictive accuracy, new layer of insights, and speed (Pillai, 2023).

2.1.2 Enhanced Market Efficiency and Accuracy

According to Fama (1970), an ideal market is referring to a market in which the prices should give guidance on making decisions in resource allocation. In short, a market may be defined as efficient when prices of the assets traded on the market fully reflect all available information. This concept is called Efficient Market Hypothesis (EMH). In such efficient market, investors are unlikely to constantly achieve abnormal returns by using publicly available data, as all relevant information is already incorporated into the current prices. Market efficiency is categorised into three degrees. Firstly, the weak form, which reflects past price information. Secondly, the semi-strong form, which reflects all publicly available information. Lastly, the strong form, which reflects all public and private information. Information is promptly and completely integrated into asset pricing in an efficient market. Pricing should reflect all available information at any given time, hence the more efficient the market, the more accurate the pricing should be.

Market accuracy refers to accurate predictions on forecasting market trends, asset prices, and economic indicators (Rehman & Bukhari, 2024). The way that financial professionals approach market forecasting is changing because of the accuracy and precision of AI-driven predictions. AI improves the ability to more accurately predict market trends, asset prices, and financial situations by utilizing advanced algorithms for machine learning and processing large information.

Shaikh et al. (2025) argues that the main advantage of incorporating AI-driven strategies in financial market, particularly stock market, is its ability to promptly and accurately analyse large amounts of data to help users carry out trades and well-informed predictions. The spectrum of data including social media, historical prices, real-time market feeds, news articles, corporate communications and other relevant insights. This computational study of vast amounts of unstructured textual data with the use of Natural Language Processing (NLP), is called sentiment analysis or opinion mining (Omoseebi, Owen, & Loveth, 2023). It is essential to perform sentiment analysis in financial market because no matter positive, negative, or neutral sentiments, they all play a significant role in influencing market movements. With the help of NLP, the process of extracting sentiment from text-based data is automated, enabling timely insights and addressing the challenge faced by human analysts in keeping up with the vast amount of information.

Despite its benefits, sentiment analysis possesses several challenges that can influence users' decision-making due to inaccuracies in sentiment extraction, including difficulties in detecting sarcasm, learning domain-specific language, and filtering out irrelevant information, as well as subjectivity in sentiment interpretation and model limitations (Yacoub, Slim, & Aboutabl, 2024).

Odeyemi et al. (2024) and Masood (2024) also agreed that AI adoption in financial markets can enhance the efficiency and accuracy of financial market through algorithmic and High-Frequency Trading (HFT). In the study by Odeyemi et. al. (2024), the integration of Machine Learning and AI in financial forecasting are analysed with the academic databases and publications from popular financial institutions. The search strategy that was implemented included key phrases with Boolean operators that were related to the topic of investigation. The study covered publications from 2010 to 2024 and only focused on English documents to study the recent trends for the past 14 years. The selection of relevant literature also involved a detailed process of setting up exclusion and inclusion criteria, which limits the study population to markets in United States, with an exception that the findings deliver useful global insights of application of AI in financial forecasting. This study highlights how AI and ML have improved financial forecasting accuracy and market efficiency, resulting in more informed decision-making. These technologies enable more accurate forecasts of asset values and market movements by analysing large datasets and applying advanced models. Financial organizations can improve risk management and portfolio optimization by making faster and more accurate investment decisions. The entire performance and stability of financial markets are eventually improved by this increased precision, which also lowers uncertainty, increases confidence, and promotes investors' capacity to react better to market fluctuations.

In Masood's research (2024), the role of AI and its pros and cons as compared to traditional financial forecasting methods were discussed along with its future potential. The research looks at how AI affects financial markets, focusing on four key areas: market efficiency, trading, risk management, and compliance. It reviews recent developments to show how AI improves market operations while also pointing out challenges and limitations. The goal is to help understand AI's impact and guide future research in this growing field. Masood (2024) did not adopt a systematic filtering method but conducted a comparative analysis to discuss the difference between AI and traditional approaches in financial markets. The findings aligned with the findings in the study by Odeyemi et. al. (2024), which mentioned that AI's capability to process high volume of data under a short period of time, providing better efficiency. Masood also claimed that AI models helped in maintaining a stable financial ecosystem, with high level of responsiveness to improve finding prices efficiency, lower transaction costs, and increase trading liquidity.

In both Odeyemi et. al. and Masood's research (2024), the future of AI was pictured clearly that AI will keep enhancing market accuracy and efficiency, which will help with financial decision-making as more accurate forecasts will be provided by transparent hybrid AI models that integrate machine learning and traditional methods. Both researches also stated that financial systems will be able to react immediately to changes in the market thanks to flexible trading techniques and real-time risk management though specialized tools like robo-advisors and personalized financial planning will offer customized guidance as AI develops, enabling customers to make wiser financial choices. However ethical issues like equity and data privacy will remain to be important.

Nevertheless, AI also has other limitations in financial markets, for instance, HFT is associated with challenges that can reduce market efficiency. Market fragmentation can result from the presence of several HFT firms in several venues, which disperses liquidity and makes it more difficult for investors to obtain the best prices. The short-term focus of HFT strategies may also heighten market volatility by amplifying price fluctuations. Additionally, the speed advantage of HFT creates opportunities for manipulative practices such as spoofing and layering, which can distort market signals and undermine fairness and integrity in trading (Nahar, Nishat, Shoaib, & Hossain, 2024).

Overall, existing studies have shown that AI serves as a tool to enhance market efficiency and accuracy, which in turn play a significant role in influencing financial market decision-making despite its challenges. AI uses advanced algorithms and large datasets to improve forecasting, trading strategies, and risk management, leading to faster and better decisions. AI's ability to analyse real-time data, automate sentiment analysis, and optimize portfolio management further contributes to market stability and investor confidence. However, despite these advancements, challenges such as algorithmic bias, data privacy concerns, and ethical issues like fairness and transparency remain crucial considerations. Additionally, the limitations of HFT and the potential for market manipulation add complexity to AI adoption in financial markets.

AI is transforming financial markets, but a balanced approach is necessary to address its challenges and ensure ethical use. In the future, combining AI models with traditional methods, creating adaptive trading strategies, and improving transparency in AI systems will be the key to better decision-making and more efficient markets. Research should focus on improving AI technology, solving ethical issues, and developing new rules that keep up with AI's fast growth in finance. This will be crucial to make sure AI helps financial markets while keeping things fair, transparent, and dependable.

2.1.3 Reduction in Human Bias

Sattar et al. (2020) argues that the process of decision making in financial market not only depends on the situation and environment variables, but it also involves the psychological behaviour of investors. According to Shaikh et al. (2025), investors decision making in financial market is often influenced by various of cognitive bias, namely emotional decision-making, overconfidence, and herd mentality.

According to Zahera and Bansal (2018), confirmation bias is used to describe people who have a pre-established impression of something, and they fully rely on that information. This leads them to modify future information to align with their views, resulting in irrational decisions are made by investors as they are inclined towards the information they have and avoid other evidence that contradicts them. Furthermore, Cheng (2018) defines confirmation bias as investors’ tendency to ignore information that are inconsistent with their pre-existing beliefs. This behaviour may cause investors to selectively take in information that supports their expectations while neglecting important insights that could hinder them from making informed financial decisions.

A descriptive research conducted by Shukla & Shukla (2025) examined the influence of confirmation bias and other cognitive biases on investment decision-making among 506 retail investors from the Bombay Stock Exchange in India. The results show that all four biases including confirmation bias have significant impact on investment decisions of investors.

Overconfidence is a cognitive bias that is defined as the tendency of investors to overestimate their knowledge, skills, and abilities when making financial decisions (Grežo, 2020). It refers to the state in which people believe they have sufficient information to make wise investment decisions. They also tend to relate the high performance of the market to their own performance, neglecting the possibility of ignoring other factors that can make them incur significant loses while focusing too much on their own capabilities.

According to Singh, Malik, Jain, & Abouraia (2024) overconfidence can cause investors to take unnecessary risks or make bad decisions if they believe they are more knowledgeable or experienced than they actually are. Hence, investors must be able to identify and address overconfidence bias since it might impair their decision-making and long-term investment success.

According to Ayoub and Balawi (2022), herd behaviour refers to the phenomenon where individuals in a group act according to the behaviour of the group without own judgement and knowledge. This is because the decisions made by the majority are assumed to be always correct (Bakar & Yi, 2016). In the context of financial market, for example, stock market, many investors are misguided in imitating crowd actions of buying and selling, causing irrational decision-making.

AI, namely machine learning and data analytics, has revolutionized the way that financial decisions are made. Vast volumes of data may be processed by AI systems, which can then spot trends and forecast outcomes, giving investors insightful information (Omoseebi, Owen, & Loveth, 2023). Significant instances include algorithmic trading, robo-advisors, and sentiment analysis tools. AI's ability to enhance decision-making accuracy and efficiency in financial markets without being influenced by emotional biases could significantly help in mitigating the impact of irrational decision-making that often causes by emotional factors (Rehman, Dhiman, & Cheema, 2024).

The study by Rehman et. al. (2024) explores the growing influence of robo-advisors and AI in investment decision-making and how these technologies can help reduce behavioural biases commonly exhibited by human investors. The major finding is that AI, particularly robo-advisors, has the potential to reduce human emotional and cognitive biases, resulting in more reasonable and objective financial judgments.

AI systems which are powered by advanced algorithms, machine learning, and data analytics, analyse large volumes of market data without the influence of emotions such as fear, greed, or overconfidence. This objectivity allows AI to generate data-driven investment recommendations, helping investors avoid impulsive or irrational decisions that are often rooted in behavioural biases like loss aversion, herd mentality, or confirmation bias. Investors with stronger emotional intelligence are more likely to successfully evaluate and apply AI-generated insights. This establishes a symbiotic relationship in which emotionally aware investors may work more effectively with AI systems, improving overall decision-making outcomes.

Another study by Kavitha et. al. (2025) also agreed that AI helps in reducing the possibility of human emotional bias and errors while making financial decision. AI-based algorithms reduce subjective biases including confirmation bias, herd mentality, and overconfidence by using objective, reliable, and data-driven techniques. Additionally, the likelihood of human mistake related to manual data entry, transaction processing, and calculation errors decreases substantially when routine jobs are automated by AI.

In order to mitigate the human bias and error, several strategies are implemented in AI decision-making. Data-Centric, algorithmic and human-centred approaches were developed to make AI more reliable and accurate while involving in the decision-making process. Charkra et al. (2024) found that human biases influence the shaping of AI systems and affect their performance in decision-making. However, their study also revealed that the mitigation strategies can reduce the bias but with some side effects on model accuracy and performance.

In conclusion, the study shows that AI and robo-advisors are changing the financial sector by providing a more rational, flexible, and consistent approach to investment decisions. AI improves decision-making quality while reducing the impact of emotional biases, leading to increased market stability and efficiency. These benefits must be balanced with ethical governance and transparency to fully achieve AI's potential in the financial industry.

2.1.4 Personalized Investment Strategies

Automated investment managers, or robo-advisors, have emerged as an alternative to traditional financial advisors. The viability of robo-advisors crucially depends on their ability to offer personalized financial advice.

Capponi et al. (2019) presents a personalized robo-advisory model that integrates AI with interactive portfolio optimization to enhance investment decision-making in financial markets. Their study introduces a dynamic framework where the AI system continuously updates investment strategies based on client-specific feedback, risk preferences, and behavioral inputs. The study's mean-variance optimization model, adjusted for evolving investor responses, demonstrates how adaptive strategies can better align portfolios with changing financial goals. This hybrid approach merges quantitative finance with behavioral interaction modeling, emphasizes AI 's ability to automate and customize advisory services while increasing investor engagement. This research contributes to the field by highlighting the potential of AI to both automate and customize financial advisory services, offering a more responsive and client-centric investment experience. It also suggests that personalization through AI can foster greater trust and satisfaction in financial markets, which is essential for the widespread adoption of robo-advisory systems.

According to Fields et al. (2025), personalized financial advisory involves tailoring investment strategies and financial advice based on an individual's financial goals, risk preferences, and behavioral characteristics. The study uses a quasi-experimental design with surveys, interviews, and performance metrics such as ROI and Sharpe ratio to evaluate the effectiveness of robo-advisors. These AI-powered platforms offer scalable, low-cost, and customized investment advice with minimal human input, analyzing user data to generate personalized portfolios. Initially targeted at retail investors, robo-advisors have evolved to include advanced features such as tax optimization and socially responsible investing. Deep learning demonstrated the highest alignment with investor goals (88% accuracy) among the machine learning models, with SVM achieving 82% and decision trees 78%. Furthermore, the study also emphasizes that while they improve satisfaction and accessibility, concerns remain over algorithmic bias, limited transparency, and data privacy. Robo-advisors may also struggle to capture human factors such as emotional responses to market events or life-stage changes that influence investment decisions. The study advocates for integrating Explainable AI (XAI) techniques and hybrid advisory models that combine AI capabilities with human judgment that offer the most effective path forward for personalized investment decisions.

Falsetti (2025) investigates the impact of AI-driven robo-advisors on both the decision-making process and the personalization of investment strategies, highlighting their growing role in modern financial advisory services. The study explores how different categories of AI such as Mechanical AI, Thinking AI, and Feeling AI are applied to enhance customer satisfaction by tailoring investment strategies for decision making to individual preferences, financial goals, and risk tolerance. This research emphasizes that by using algorithms such as genetic programming and behavioural modelling, robo-advisors demonstrate up to a 30% improvement in portfolio fitness compared to traditional methods. The thesis also examines recommendation systems, including collaborative filtering, Key Performance Indicator (KPI) predictors, and hybrid models, which personalize investment strategies by analyzing user preferences and historical data. Additionally, AI is shown to reduce behavioral biases such as overconfidence, promoting more rational decision-making. Despite these advantages, the study raises concerns about data privacy, algorithmic transparency, and ethical risks. The author advocates for the use of explainable AI and hybrid advisory models that combine algorithmic precision with human oversight. The findings conclude that AI-powered robo-advisors significantly improve accessibility, personalization, and decision quality for both novice and experienced investors.

Overall, these studies demonstrate that AI plays a transformative role in advancing personalized investment strategies by enhancing automation, improving portfolio alignment, and increasing accessibility for diverse investor profiles.

2.1.5 Ethical and Regulatory Challenges

According to Gupta et al. (2025) the proper use of AI technology requires adherence to ethical standards. The use of models and algorithms in decision-making raises concerns on accountability, transparency, as well as algorithmic bias. However, ethical and regulatory challenges emerge when AI systems make significant financial decisions without adequate human oversight, transparency, or fairness.

Owolabi et al. (2024) investigated one of the primary ethical concerns in AI is algorithmic opacity, commonly referred to as the "black box" problem. The complexity and non-transparency of AI models make it difficult for financial institutions and regulators to understand how decisions are made, thereby hindering efforts to ensure accountability and auditability. This lack of explainability raises serious concerns about transparency and trust, especially in environments where financial outcomes significantly impact individuals and businesses. Furthermore, the study highlights the issue of bias and fairness, noting that AI models can inherit historical biases present in their training data, which can lead to discriminatory outcomes in financial decision-making. This study also states that these concerns are compounded by the dynamic and evolving nature of AI, which presents challenges for traditional regulatory frameworks that are typically slower to adapt than the pace of technological advancement. Additionally, financial institutions must operate within strict legal frameworks such as the General Data Protection Regulation (GDPR), while simultaneously leveraging Big Data for improved analytics and decision-making. Thus, the challenge lies in balancing innovation with ethical responsibility and legal compliance is essential to safeguard consumer rights and ensure trust in AI-driven financial systems.

The AI and Risk Management (2025) based on a cross-European study by Deloitte, supports these findings and reveals that ethical AI governance remains at an early stage across the financial sector. Many institutions lack robust governance frameworks to manage AI risks effectively. The report emphasized the need for transparency, explainability, and auditability, particularly in AI systems deployed in financial markets where decisions have significant regulatory and economic implications. A major challenge identified is dependence of AI performance on high-quality data, which is often compromised by legacy systems and organizational silos that prevent seamless data integration. These structural issues reduce the effectiveness and reliability of AI-driven decision-making. Furthermore, the complex architecture of deep learning models, which includes multiple hidden decision-making layers, poses serious challenges to interpretability. This makes it difficult for institutions to ensure that AI decisions align with organizational values, ethical standards, and regulatory expectations. The evolving nature of AI where models continuously learn and adapt further complicates efforts to maintain auditability and traceability. Regulatory compliance also becomes problematic, particularly under GDPR, which requires firms to provide clear justifications for automated decisions with significant impacts on individuals. The report recommends that future research focuses on developing standardized ethical compliance metrics and promote cross-industry best practices to strengthen AI governance frameworks and ensure responsible adoption across financial markets.

Challoumis (2024) critically assessed the ethical and regulatory challenges posed by the integration of AI in financial systems. The study highlights the risk of AI perpetuating social and economic biases, especially in areas such as credit scoring and investment decision-making, which could lead to discriminatory financial practices. This highlights the ethical need for fairness and inclusivity in AI model design and deployment. The study also underscores the problem of algorithmic opacity, stressing that the inability of consumers and stakeholders to understand or challenge automated decisions undermines transparency and accountability. The study further critiques the regulatory gap between fast-moving AI innovations and outdated financial governance structures, especially in cross-broader contexts. Divergent approaches to AI governance in the US and the EU illustrate deeper philosophical differences in balancing technological innovation with consumer protection. As a result, this lack of harmonization complicates legal oversight across jurisdictions and weakens safeguards. Moreover, Challoumis warns of the systemic risks introduced by AI, such as increased market volatility from high-frequency trading and the potential consequences of insufficient human oversight. To address these issues, the study advocates a principled and proactive approach, which includes the application of ethical concepts like autonomy, consent, and creator responsibility. It further recommends regular AI audits, adoption of international regulatory frameworks, and the development of ethical-by-design systems that prioritize fairness, accountability, and data privacy.

Overall, while AI offers transformative potential in financial market decision-making, it simultaneously introduces complex ethical and regulatory challenges. Common concerns include algorithmic opacity, data bias, lack of transparency and accountability, and the misalignment between fast-evolving AI technologies and slow-moving regulatory frameworks. These issues are particularly critical in high-stakes environments such as credit scoring, fraud detection, and investment advisory, where AI-driven decisions can have far-reaching impacts on individuals and institutions.

2.1.6 Market Adaptation and Technological Barriers

Reichard and Rydstrand (2025) conducted a study exploring the practical challenges financial professionals face when adopting AI technologies in investment decision-making. Despite AI's potential to enhance portfolio optimization, risk modelling, and data analysis, the authors found that real-world adoption remains cautious and fragmented. Resistance is attributed to both technological limitations and psychological and cultural factors within organizations. Traditional financial models often fail to keep pace with the complexity and scale of modern markets, prompting interest in AI. However, through a mixed-methods approach involving 25 survey respondents and five interviews with professionals across asset management, venture capital, and investment banking. The study uncovered key technological barriers such as limited model explainability, integration challenges with legacy systems, data quality concerns, and regulatory uncertainty. These factors undermine trust in AI for high-stakes decision-making, confining its use to low-risk tasks like document summarization or trial settings, and professionals remain cautious due to the risk of model error, especially in volatile markets. The study also noted that although there is optimism about AI's potential, especially for improving efficiency, actual usage is constrained by trust, infrastructure, and the need for human judgment in high-stakes decisions. This research highlights a key gap between the technical capabilities of AI and its practical implementation in real-world financial settings.

Ochuba et al. (2024) revealed that while AI is increasingly recognized for its potential to enhance investment strategies such as predictive analytics, risk control, trend identification, while its adoption remains uneven across the financial sector. Institutions with stronger technological infrastructure, sufficient financial resources, and prior exposure to AI tend to adapt more quickly and implement AI tools more effectively. In contrast, emerging economies often struggle with inadequate infrastructure, limited internet connectivity, and digital literacy gaps, all of which hinder the widespread deployment of AI-driven financial systems. These limitations are particularly problematic in regions where limited internet penetration, inadequate telecommunications infrastructure, and disparities in digital literacy and access. Key technological barriers in the study include low data quality, limited interpretability of AI models, and challenges integrating AI systems with existing legacy infrastructures. Furthermore, a lack of algorithm transparency and insufficient technical expertise further restrict AI implementation, particularly among smaller firms. The research also emphasizes the role of policies and strategic investments in supporting AI adaptation. AI-powered systems, despite these challenges, are capable of handling a wide range of repetitive and time-consuming tasks, such as data entry, document processing, and customer service inquiries, in a faster and more accurate than human counterparts. AI-powered chatbots and virtual assistants, for example, can manage real-time customer interactions, resolve queries, and support decision-making processes without requiring human intervention. This not only improves service speed and quality but also allows financial professionals to focus on higher-value tasks such as strategic planning and relationship management. Moreover, AI facilitates more efficient data analysis and predictive modeling, enabling financial institutions to extract actionable insights from large volumes of data. Machine learning algorithms can analyze patterns and trends in historical data, which supports smarter investment decisions, effective risk management, and better forecasting. For instance, AI models can analyze market data to identify trading opportunities, optimize investment portfolios, and forecast market trends with greater accuracy than traditional methods.

In the study of Bhat (2024) explores the expanding role of artificial intelligence on financial decision-making, emphasizing its growing integration across domains such as portfolio optimization, risk assessment, fraud detection, and algorithmic trading, The study highlights that AI enables financial institutions to make faster, data-driven decisions by leveraging real-time insights and predictive analytics, thereby improving operational efficiency and market responsiveness. Decision-making based on artificial intelligence provides financial managers with tools to make informed decisions, maximize profits and increase organizational efficiency. ML algorithms handle large volumes of data, enabling managers to make complex decisions more efficiently. However, despite its potential, the article identifies key technological barriers that hinder widespread adoption, including concerns about data integrity, algorithmic opacity, and lack of explainability. Regulatory compliance and the risk of systemic instability further complicate the deployment of AI in financial markets. Using a mixed-method approach, combining grounded theory, Garrett ranking, and chi-square analysis. Bhat (2024) investigates both adoption trends and implementation challenges across the financial sector. The findings suggest that successful integration of AI requires both technological readiness and ethical governance, cross-sector collaboration, and transparency. Ultimately, the study concludes that while AI has transformative potential in financial decision-making, its effective application depends on how well institutions balance innovation with accountability, particularly in dynamic and regulated market environments.

Overall, AI offers significant potential to enhance financial market decision-making through improved efficiency, predictive accuracy, and automation, its widespread adoption remains uneven. Technological barriers such as limited explainability, poor data quality, and challenges integrating AI with legacy systems continue to hinder implementation, especially in emerging markets. Additionally, psychological resistance, regulatory uncertainty, and ethical concerns contribute to a cautious approach among financial professionals.

2.1.7 Investor Perception and Trust

Investor perception in this study refers to how investors interpret and evaluate AI-based financial systems, shaped by factors such as their investment experience, the quality of the service, and the provider's reputation (Cheng et al., 2019). According to Grandison and Sloman (2009), trust is defined as "the firm belief in the competence of an entity to act dependably, securely, and reliably within a specified context". In this context, trust refers to the extent to which investors believe that robo-advisors are honest, capable, and work in their best interest (Cao et al., 2025). Therefore, investor perception will directly influence trust. Once trust is established, investors are more likely to rely on AI in their financial market decision-making (AlAmayreh et al., 2023).

Recent studies indicate that although investors are increasingly open to integrating AI into financial market decision-making, their willingness to adopt AI remains conditional (Luo et al., 2024). Consequently, investors' perception and trust play an important role in shaping their behavior towards the intention to adopt AI in financial market decision-making.

According to Cheng et al. (2019), they found that investors in China will only develop trust when they perceive a high level of several factors, based on findings from qualitative interviews and quantitative analysis. These factors include provider reputation, consistent information quality, service quality, service commitment, government regulation and attitude toward AI, and supervisory control. When investors perceive a high level of these factors, they are more likely to build strong trust and intention to adopt AI-generated financial advice. Additionally, the study showed that junior investors (with less than 2 years of investment experience) tend to prioritize service quality. The more satisfied they are with the service, the greater trust they put in AI. Conversely, senior investors (with more than 2 years of investment experience) are less influenced by service-related factors. Instead, they relied more on their knowledge and independent judgment. This study highlights that the willingness to adopt AI in financial market decision-making is conditional upon the perceived quality and credibility of the service.

Similarly, a study by Ting et al. (2023) involving 178 investors in Taiwan examined how investor perception and trust affect AI adoption in financial market decision-making. The researchers created two versions of reports using OpenAI's ChatGPT, one with only macroeconomic and financial data, namely V1, while the other incorporates both data and news content, namely V2. Both versions were perceived as professional, but V2 was rated higher. As a result, investors showed a stronger willingness and trust to invest using insights from V2 compared to V1. Furthermore, the study found that general investors held more positive perceptions of AI-generated reports, which significantly increases their trust and willingness to adopt AI-driven recommendations. In contrast, financial professionals' distrust reduces the reliance on AI. This highlights the persuasive power of AI in financial market decision-making, especially when reports are data-rich and contextually detailed, while also revealing the divide between general investors and financial professionals.

Moreover, Cao et al. (2025) conducted a qualitative study at Australian universities and found that trust in robo-advisory is formed when meeting certain factors, such as technology trust, provider reputation, and system trust, which aligns with the study conducted by Cheng et al. (2019). Besides technical factors, the study reveals that trust can also be shaped by social influence, psychological comfort, safeguarding, and personal capabilities. The study revealed that many individuals prefer to seek additional confirmation from human advisors. This preference might be due to poor risk tolerance and financial literacy. Human interactions will help them build a foundation of trust in using AI to make decisions in the financial market. However, concerns such as data privacy and a lack of algorithmic transparency that potentially lead to financial losses can erode investors' trust in AI. Hence, this study highlighted the need for a comprehensive strategy in order to build trust in AI adoption in financial market decision-making.

Overall, the existing studies demonstrate that investor perception and trust significantly influence the intention to adopt AI in financial market decision-making. These studies show that while many investors are willing to perceive the benefits of AI and develop trust in using AI in the financial market, the willingness is conditional. Therefore, these findings highlight both the opportunities and the challenges in the expansion of using AI in the financial market decision-making.

2.2 Theoretical Framework

2.2.1 Diffusion of Innovations Theory

The Diffusion of Innovation Theory (DoI), developed by Rogers in 1995, is used to study the factors that affect an individual's acceptance of an innovation. This theory proposes five key factors that influence the adoption of any innovation, which are relative advantage, complexity, compatibility, trialability, and observability. Firstly, relative advantage refers to the usefulness of an innovation compared to what the adopter is already using. Secondly, complexity is the degree to which an innovation is perceived as relatively difficult to understand and use. Next, compatibility indicates how well the innovation fits with adopter values, habits, and past experiences. Moreover, trialability is trying out or testing an innovation so that it makes meaning to the adopter. Lastly, observability is the degree to which the results of an innovation are visible to others (Olatokun & Igbinedion, 2009).

The first independent variable is enhanced market efficiency and accuracy, which is directly related to the factor of relative advantage and observability from the Diffusion of Innovation Theory. This means that when investors see that AI-driven techniques allow investors to act more accurately, faster, and analyze risk more effectively compared to traditional methods, they will recognize the benefits of AI-driven techniques in the financial market decision-making. These noticeable improvements have attracted more investors to adopt AI in the financial market.

Next, reduction in human error and bias enhances both relative advantage and compatibility in the Diffusion of Innovation Theory, directly impacting the use of AI for financial market decisions. This is because AI aligns with investors' expectations for accuracy, fairness, and data-driven outcomes. Also, AI provides more objective and consistent decisions compared to traditional human-based methods by minimizing biased human judgment. These capabilities increase investors' confidence in using AI in financial market decision-making.

The third variable is personalized investment strategies, which refers to AI's ability to offer client-specific portfolio solutions. This independent variable not only strengthens relative advantage but also increases perceived complexity. This is because the advanced algorithms require financial professionals to develop new skill sets and trust when using AI to make decisions in the financial market. For example, robo-advisors like StashAway use AI to customize portfolios based on individual financial goals and risk tolerance. However, understanding and managing this tool can be challenging for investors who are unfamiliar with using new technology. In summary, personalized investment strategies by using AI can enhance relative advantages. On the other hand, the technical complexity of AI can also lead to slow adoption of AI.

Furthermore, ethical and regulatory challenges are significant barriers to AI adoption in the financial market because they increase complexity and reduce the compatibility of the Diffusion of Innovation Theory. Investors must ensure that the AI-driven techniques that they use in investment are aligned with legal standards, fairness, and avoid discriminatory outcomes. However, AI decision-making processes are not transparent, which makes it difficult to explain or justify their decisions and increases the risk of non-compliance. Hence, this has increased the concerns about ethical responsibility, accountability, and transparency.

The fifth variable, which is market adaptation and technological barriers, is directly related to the complexity factor in the Diffusion of Innovation Theory. For example, financial firms that lack technological infrastructure or digital readiness may experience delays in the adoption of AI. Thus, the diffusion process can be slowed down if the perceived complexity is high due to the inadequate infrastructure and technological capabilities.

Lastly, the factor that best fits investor perception and trust is observability. When the result of using AI in financial market decision-making is good and visible, investors will build trust in the adoption of AI. For instance, the result of using AI to decide on the financial market can improve returns and reduce risks. Investors will perceive the advantages of using AI and boost confidence in AI, which further leads to developing trust in the adoption of AI. In contrast, if investors perceive a bad outcome from using AI, they are unlikely to develop trust. Therefore, investor perception and trust are influenced by the observability of AI outcomes, which play an important role in the diffusion process.

In conclusion, each independent variable plays an important role in shaping how AI is adopted by linking to different factors of Rogers's Diffusion of Innovation Theory.

2.3 Conceptual Framework

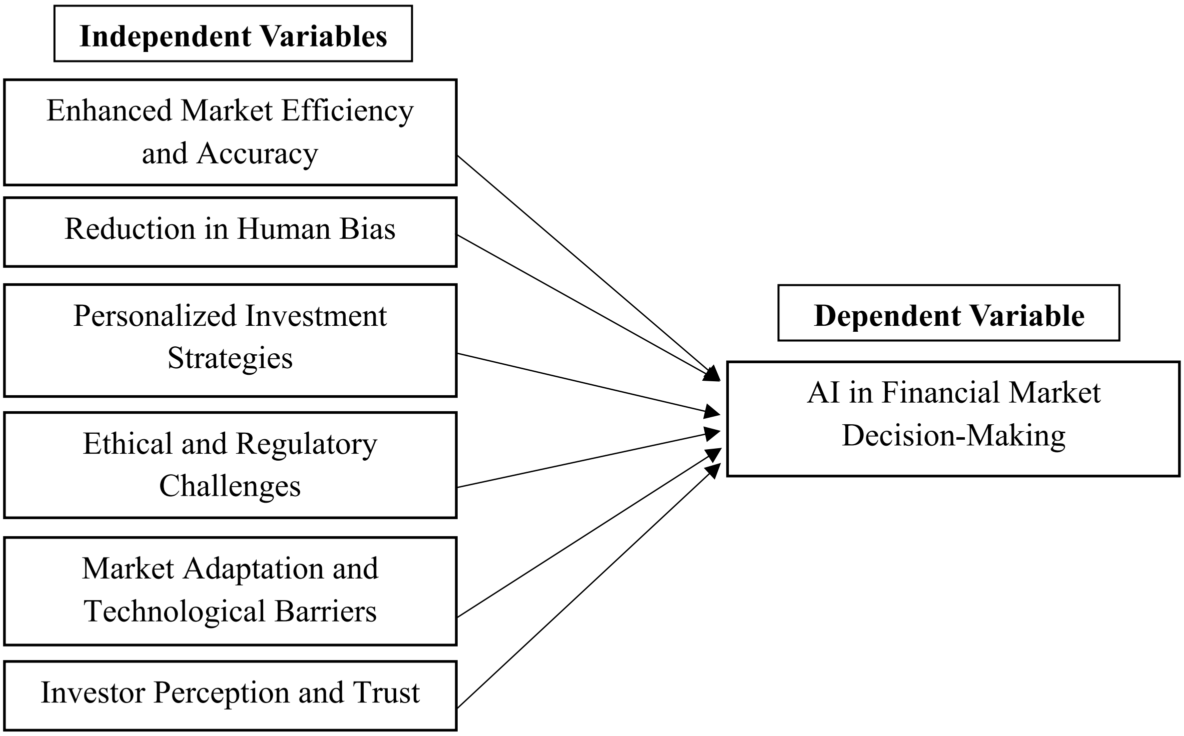


Figure 2.1: *Conceptual Framework*

A conceptual framework to examine AI in financial market decision-making is presented. This conceptual framework considers six factors which are enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust. According to the previous studies, these independent variables are expected to have a significant impact on adoption of AI in financial market decision-making. Hence, this framework will be used in the following section to develop hypotheses and evaluate the accuracy of the inferences.

2.4 Hypothesis Development

2.4.1 Enhanced Market Efficiency and Accuracy towards Intention to Adopt AI in Malaysia’s Financial Market Decision-Making

Based on previous research, studies have found that enhanced market efficiency and accuracy has a significant influence on the intention to adopt AI in financial market decision-making despite the implications. For example, studies from both Odeyemi et al. (2024) and Masood (2024) highlight how AI and machine learning improve financial forecasting accuracy, resulting in better-informed decision-making, improved risk management, and more efficient market operations. They also stress that AI's ability to process large datasets quickly enhances market efficiency and allows for more accurate predictions, which in turn improves financial decision-making.

H_1: There is a significant relationship between enhanced market efficiency and accuracy and intention to adopt AI in financial market decision-making.

2.4.2 Reduction in Human Bias towards Intention to Adopt AI in Malaysia’s Financial Market Decision-Making

The studies that agree that AI can mitigate human bias in financial decision-making include those by Rehman et al. (2024) and Kavitha et al. (2025). Both studies emphasize the role of AI, particularly robo-advisors, in reducing emotional and cognitive biases such as confirmation bias, overconfidence, and herd mentality, which then further influence investors’ intention to adopt AI in financial market decision-making.

H_1: There is a significant relationship between reduction in human bias and intention to adopt AI in financial market decision-making.

2.4.3 Personalized Investment Strategies towards Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Based on previous research, several studies have found that personalized investment strategies have a significant influence on the intention to adopt AI in financial market decision-making. For example, Capponi et al. (2019) and Fields (2025). Both studies suggest that personalized AI systems not only enhance investment outcomes but also play a critical role in encouraging adoption by aligning financial decisions more closely with individual investor goals, behavior, and risk preferences.

H_1: There is a significant relationship between personalized investment strategies to adopt AI in the financial market decision-making

2.4.4 Ethical and Regulatory Challenges towards Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Based on previous research, the studies have found that ethical and regulatory challenges have a significant influence on the intention to adopt AI in financial market decision-making include those by AI and risk management (2025), and Challoumis (2024). These studies highlight how issues such as algorithmic opacity, lack of explainability, data bias, and outdated regulatory frameworks create barriers to trust, transparency, and accountability which are the factors that directly impact institutions' willingness to adopt AI technologies in financial decision-making.

H_1: There is a significant relationship between ethical and regulatory challenges to adopt AI in the financial market decision-making

2.4.5 Market Adaptation and Technological Barriers towards Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Based on previous research, the studies that agree that market adaptation and technological barriers have a significant influence on the intention to adopt AI in financial market decision-making include those by Reichard and Rydstrand (2025), and Ochuba et al. (2024). These studies highlight how challenges such as poor data quality, infrastructure limitations, legacy system integration, and regulatory uncertainty can slow down the effective adoption of AI.

H_1: There is a significant relationship between market adaptation and technological barriers to adopt AI in the financial market decision-making

2.4.6 Investor Perception and Trust towards Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Based on the previous research, studies have found that investor perception and trust have a significant influence on the intention to adopt AI in financial market decision-making in several countries, such as Taiwan (Ting et al., 2023), China (Cheng et al., 2019), and Australia (Cao et al., 2025).

H_1: There is a significant relationship between investor perception and trust and intention to adopt AI in the financial market decision-making

2.5 Summary

To sum up, this chapter reviewed the existing literature on six independent variables (enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust), as well as the dependent variable (AI in financial market decision-making). Moreover, the theoretical framework and conceptual framework have also been studied in this chapter. Lastly, several hypotheses were developed to be tested in the following chapter.

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

This study seeks to examine if enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust can significantly affect the intention to adopt AI in the Malaysian financial market decision-making. This chapter presents the research methodology, including research design and data collection methods, followed by data processing and analysis techniques.

3.1 Research Design

According to Asenahabi (2019), research design serves as a framework for conducting an extensive study to achieve the research objectives. It is an investigation that gives precise guidance for research processes. Research design is normally categorized into three main types, namely mixed method research design, qualitative, and quantitative.

An investigation into an issue that has been identified through the testing of theory, with variables are measured and analysed numerically using statistical methods is known as quantitative research (Gupta & Gupta, 2023). Its purpose is to measure the data and generalize the findings from a study sample from several viewpoints

(Ghanad, 2023). This approach is often employed in fields such as natural and social sciences, where data are often collected through surveys and statistical analysis (Bhandari, 2023).

Thus, it is appropriate to do quantitative research in this study in order to examine how enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust significantly affect the intention to adopt AI in the Malaysian financial market decision-making. Online questionnaires will be distributed through various social media platforms via Google Forms. Fixed-alternative questions are utilised in the survey, providing respondents with a predetermined set of response options (Schoonenboom, 2023).

3.1.1 Data Collection Method

The process of gathering, assessing, and analysing precise understandings for research using standard and validated methods is referred to as data collection (Mazhar, 2021). In this study, primary data is utilized for data collection.

3.1.2 Primary Data

According to Ajayi (2023), primary data refers to the firsthand data that is collected by the researchers. Primary data sources include questionnaires, personal interviews, surveys, observations, experiments, and so on. Also, primary data refers to up-to-date information collected specifically to address a current problem (Ajayi, 2023).

In this research, a structured questionnaire was created and distributed to Malaysian investors through Google Forms in order to examine how the six variables will influence the intention to adopt AI in Malaysia's financial market. The use of primary data is appropriate because it ensures that the information reflects the current market situation in Malaysia. Moreover, collecting primary data ensures the findings are directly relevant to the Malaysian context.

3.2 Sampling Design

3.2.1 Target Respondents

The target respondents of this study are individuals who are investors in Malaysia's financial market, particularly those aged 18 and above, who have experience in utilizing Artificial Intelligence (AI) applications such as robo-advisors, algorithmic trading platforms, and other AI-enabled investment tools to support their financial decision-making (MyGOV – Government of Malaysia's Official Portal, n.d.).

3.2.2 Sampling Location

Geographical area where data is collected is known as the sampling location. For this study, Malaysia was selected as the sampling location, as the target respondents are individuals residing in Malaysia who engage with financial markets.

3.2.3 Sampling Elements

The sampling elements refer to the specific units of the population that are chosen to provide the required data. In this study, the sampling elements consist of individual investors who are ages 18-year-old and above, participate in Malaysian financial market have involved in financial decision-making.

3.2.4 Sampling Size

In response to the increasing demand for research, the National Education Association has developed a formula for determining sample size needed to represent a given population (Krejcie & Morgan, 1970). As of 31 July 2025, the estimated population of Malaysian aged from 15 to 60 years and above by Department of Statistics Malaysia data is 13.4 million *(Refer to Appendix 3.1)*. Hence, based on the 'Table for Determining Sample Size from a Given Population' *(Refer to Appendix 3.2)*, the minimum required sample size for this study is roughly 384.

3.2.5 Sampling Technique

This study adopted purposive sampling, a type of non-probability sampling method as the sampling technique. Purposive sampling is also known as judgmental, selective, or subjective sampling (Rai & Thapa, 2015). This sampling technique aims to concentrate on particular population traits that are pertinent to the research, hence not everyone has equal chance to participate in the research (Rai & Thapa, 2015). According to Alvi (2016), purposive sampling is adopted when the criteria of the target population are predefined. In this study, the criteria of the target respondents of this study were predetermined. For instance, the respondents must be individuals who are investors in Malaysia's financial market, particularly those aged 18 and above, and have experience in utilizing Artificial Intelligence (AI) applications such as robo-advisors, algorithmic trading platforms, and other AI-enabled investment tools to support their financial decision-making. Only those respondents who meet these criteria will be included in this study. Hence, purposive sampling is the most suitable sampling techniques for this study.

3.3 Research Instrument

3.3.1 Questionnaire

A research questionnaire is a set of questions or items intended to gather information from respondents regarding their views, attitudes, knowledge, opinions, and behaviour (Caduff & Ranganathan, 2023).

Questionnaires are one of the most widely used instruments for collecting primary data (Parajuli, 2004). Unlike personal interviews that produce large amounts of narrative material that takes time to summarize and interpret, questionnaires can yield quantitative data that is usually easy to tabulate, making the data easy to be analyzed (Patten, 2016). In addition, employing questionnaires as a tool enables efficient data collection from targeted respondents even if they are geographically distant (Parajuli, 2004). Moreover, questionnaires encourage more honest answers from the respondents as they can be administered anonymously, resulting in good response rates (Marshall, 2005). Thus, questionnaires are particularly suitable for this study that aims to collect respondent's intentions to adopt AI in the financial market.

The survey questionnaire for this study contains seven sections. Section A consists of seven demographic questions which include gender, age group, highest education level, employment status, investment experience, monthly investment amount in RM, and experience with AI in financial market decision-making. Sections B to G focus on items that assess respondents' intention to adopt artificial intelligence in financial market decision-making, along with the key factors that influence this intention. All responses are measured using a 5-point Likert scale to assess the respondents' views for each statement, ranging from agreement to disagreement.

3.3.1.1 Self-constructed Questionnaire

Prior to developing a questionnaire for a study, it is advisable for researchers to check the availability of pre-established validated questionnaires that might be adapted and utilized for the study (Ranganathan & Caduff, 2023). This method is called adaptation, and it provides advantages such as time and resource efficiency (Ranganathan & Caduff, 2023). However, as mentioned before, most of the existing studies on AI in the Malaysia financial market remain conceptual and lack of pre-existing validated questionnaires. Hence, a self-constructed questionnaire was developed based on relevant literature for this study *(Refer to Appendix 3.3)*. The instrument was tested for validity and reliability as it needs to be reliable and valid (Ranganathan & Caduff, 2023). As a result, the content validity was done by three experts in banking industry who are also an investor, while the reliability of the instrument is tested during pilot test with Cronbach Alpha.

3.3.2 Pilot Test

According to Van Teijlingen and Hundley (2001), pilot tests are utilized to assess the effectiveness of research instruments. Moreover, assessing respondents' familiarity with the questionnaire's terminology is one of the primary objectives of conducting a pilot test (Simkus, 2023). In addition, a pilot test is described as a preliminary investigation that is performed in research to ensure validity (Gani et al., 2020; Dikko, 2016). This is because pilot tests help to facilitate researchers in identifying possible problems in research instruments in earlier stage (Dikko, 2016). Hence, conducting pilot tests for this study before collecting data from the targeted sample is essential.

In this study, pilot test is conducted among 30 respondents to study to examine how enhanced market efficiency and accuracy, reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust significantly affect the intention to adopt AI in the Malaysian financial market decision-making. Researchers distributed the questionnaire to 30 targeted respondents through social medias such as WhatsApp and Microsoft Teams. After collecting the data from these 30 respondents, a reliability assessment and measurement of the questionnaire were conducted through SPSS27.0.

Table 3.1: *Pilot Test's Cronbach Alpha Reliability Analysis*

Variable	Variable Name	Number of Items	Cronbach's Alpha
AI	Intention to Adopt AI in Financial Market Decision-Making	5	0.876
RHB	Reduction in Human Bias	5	0.920
PIS	Personalized Investment Strategies	5	0.876
ERC	Ethical and Regulatory Challenges	5	0.858
MATB	Market Adaptation and Technological Barriers	5	0.864
IPT	Investor Perception and Trust	5	0.928
EMEA	Enhanced Market Efficiency and Accuracy	5	0.907

Table 3.1 shows pilot test's reliability analysis. According to the rules of thumb of Cronbach Alpha, AI, PIS, ERC and MATB show good reliability test results, while RHB, IPT and EMEA show excellent reliability test results. This indicates that the data is reliable and can proceed to collect data from the targeted respondents.

3.4 Construct Measurement

3.4.1 Scale of Measurement

According to CliffsNotes (2024), scale of measurements is referred to as the definition and classification of variables and numbers. The four scales of measurements include ordinal, nominal, interval, and ratio. The suitability of using particular statistical analyses is determined by the characteristics of each scale of measurement (CliffsNotes, 2024). This study mainly employed three measurement scales, namely nominal, ordinal, and interval scales.

3.4.1.1 Nominal Scale

According to Bhattacherjee (2012), nominal scales are used to measure categorical data. These scales are employed when the variables' attributes are mutually exclusive and there is no hierarchy between the groups. In this study, a few questions under Section A employed nominal scale. Those questions are related to variables such as gender, employment status, and primary investment products.

Example of nominal scale question:

Gender: Female ( ) Male ( )

3.4.1.2 Ordinal Scale

Ordinal scale is defined as a scale that uses labels to categorize cases into ranked categories (CliffsNotes, 2024). Anjana (2021) also mentioned that the variables are arranged in a specific order rather than just naming them. In this study, a few questions under questionnaire Section A employed an ordinal scale, including age, highest education level, investment experience, familiarity with AI in financial market decision-making, and monthly investment amount.

Example of ordinal scale question:

Age : 18-25 ( ) 26-35 ( ) 36-45 ( ) Above 45 ( )

3.4.1.3 Interval Scale

The definition of an interval scale is a scale created by units of equal size (CliffsNotes, 2024). Due to the arbitrary nature of zero, ratios of values are meaningless (CliffsNotes, 2024). In other words, the value 0 does not represent the complete absence of the characteristics being measured (Anjana, 2021). According to Salkind (2010), Likert scale is one of the interval scale measurement that is widely used in research as it helps to capture perceptions and opinions of the participants. In this study, Likert scale is employed in questionnaire Section B to Section H to capture the thoughts of targeted participants.

Example of Likert scale question:

Question	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
I believe AI enhances the quality of predictions in financial market trends.	1	2	3	4	5

3.5 Data Analysis

Data analysis is a crucial component in both qualitative and quantitative research. It involves process of inspecting, cleansing, transforming, and modelling data with the aim to discover useful information that can be used to enhance knowledge, proposing conclusions, and contributing to decision-making (Dibekulu, 2020). Among the statistical software that are available for performing statistical analysis, Statistical Package for Social Sciences (SPSS) is the most suitable for this study.

This is because the SPSS statistical software allows researchers to easily perform both parametric and non-parametric comparison analysis (Ong & Puteh, 2017). On top of that, it allows researchers to check the assumptions of the tests, namely normality test and outlier test. Moreover, SPSS could easily perform the Pearson's Correlation test, reliability tests, multicollinearity test, and inferential analysis, which make it an ideal software for this study. Thus, this study employs SPSS27.0 for data analysis.

3.5.1 Descriptive Analysis

Descriptive analysis is also commonly known as descriptive analytics or descriptive statistics (PESTLEanalysis Team, 2020). It refers to the process of collecting, describing, and summarizing a specific dataset collected using statistical techniques (PESTLEanalysis Team, 2020). It transforms complex quantitative insights into simple descriptions, allowing researchers to gain helpful information from the summarized data without making any conclusions (Hayes, 2024). Data in descriptive statistics are commonly presented by measures of central tendency, namely the mean, median, and mode. Moreover, data distribution measures such as standard deviation and variance; tables and graphs (Rahayu et al., 2024). The demographic information of the selected sample will be derived from Section A of the questionnaire and then assessed using descriptive analysis as demographic information is quantitative in nature.

3.5.2 Scale Measurement

3.5.2.1 Reliability Test

According to Imasuen (2022), one of the essential components of research is the estimation of reliability. It is the extent to which an experiment, test, or any measuring procedure yields the same result on repeated trials. Cronbach's Alpha is one of the most popular objective measures of reliability (Tavakol & Dennick, 2011). It is a coefficient of internal consistency that measures the extent to which items in a test assess the same underlying construct.

Since most of the questions in the questionnaire employ a five-point Likert scale, Cronbach's Alpha is the most appropriate formula to measures the internal consistency of the items according to the rule of thumb.

Table 3.2: *Rules of Thumb for Cronbach's Alpha Coefficient*

Reliability Level	**Cronbach's Alpha Range**	**Interpretation**
Excellent	0.90 and above	Indicates very high internal consistency.
Good	0.80 – 0.89	Reflects strong internal consistency.
Acceptable	0.70 – 0.79	Indicates acceptable internal consistency.
Questionable	0.60 – 0.69	Reflects questionable internal consistency.
Poor	Below 0.60	Indicates poor internal consistency.

Source: Ahmad et al. (2024)

3.5.3 Preliminary Data Screening

3.5.3.1 Multicollinearity Test

Multicollinearity poses when more than one independent variables in a regression model are themselves highly correlated, not only with the dependent variable (Shrestha, 2020; Investopedia, n.d.). Subsequently, unreliable results are produced (Investopedia, n.d.). Among different methods used to detect multicollinearity within the full regression model, this study employs Variance Inflation Factor (VIF). According to (Team, 2025), in the event of VIF is equal to 1, it indicates that the independent variables are uncorrelated. On the other hand, if the VIF falls between 1 and 5, independent variables are deemed to be moderately connected; if it is greater than 5, they seem to be highly linked. The higher VIF refers to a higher likelihood of multicollinearity, indicating extensive research is required. A value in excess of 10 in the VIF indicates severe multicollinearity, which has to be corrected.

3.5.3.2 Normality Test

Roni and Djajadikerta (2021) discuss that normality testing is an initial procedure in statistical analysis that determines whether a data set has a normal distribution. In an effort to attain normality, all variables must have a normal distribution. A serious violation of the normality assumption can raise a question on the accuracy and stability the analysis results. Researchers often assess the normality visually through the eyeball test, where the graph appears to be bell curve shaped when data distribution looks approximately normal. This method is useful for sample size larger than 50, while the formal normality tests including Shapiro-Wilk test and Kolmogorov-Smirnov test are sensitive for small to medium sized sample ($n<300$) (Kim, 2013). However, this study will employ another way of assessing normality, which is utilizing skewness and kurtosis to obtain relatively accurate indication of normality. Kurtosis values of -7 to +7 and skewness values of -2 to +2 are usually seen as acceptable (Abu-Bader, 2021).

3.5.4 Inferential Analysis

Inferential analysis involves analysing sample data to draw conclusions, derive inferences and generalize a larger targeted population based on collected data from a sample (Rahayu, Muktiarni, & Hidayat, 2024). In this study, Pearson Correlation and multiple linear regression analysis will be used to investigate whether the DV is significantly influenced by the IVs.

3.5.4.1 Multiple Linear Regression Analysis

A statistical method for identifying the relationships between a dependent variable and two or more independent variables is called multiple linear regression (Investopedia, n.d.). In this study, multiple linear regression will be utilized to test hypotheses about the relationships between the dependent and independent variables, providing insights into the population being studied (Abu-Bader, 2021).

Multiple Linear Regression Equation:

$$AI_i = \beta_0 + \beta_1 EMEA_i + \beta_2 RHB_i + \beta_3 PIS_i + \beta_4 ERC_i + \beta_5 MATB_i + \beta_6 IPT_i + \mu_i$$

Where:

AI_i = Intention to Adopt AI in Malaysia's Financial Market Decision-Making

$EMEA_i$ = Enhanced Market Efficiency and Accuracy

RHB_i = Reduction in Human Bias

PIS_i = Personalized Investment Strategies

ERC_i = Ethical and Regulatory Challenges

$MATB_i$ = Market Adaptation and Technological Barriers

IPT_i = Investor Perception and Trust

μ_i = Error term

3.5.4.2 Pearson Correlation

Pearson is a statistical method commonly used to measure the strength of association between two variables (Stewart & Ken, 2026). The correlation coefficient ranges from -1 to +1. A negative value indicates a negative correlation where a positive value indicates a positive correlation, and a value of 0 indicates there is no linear relationship between the variables. Values close to -1 or +1 respectively represent strong negative or positive linear relationships (Turney, 2024).

3.6 Summary

In summary, this chapter has explained the methods employed to conduct the research, ensuring that the research process is systematic and reliable. These methods including the research design, sampling design, research instruments, measurement of scale, and data analysis approach. Subsequently, SPSS27.0 will be utilized to run the data.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The purpose of data analysis is to examine and understand the collected data utilizing SPSS version 27. There is a total of 403 respondents aged 18 and above with experience in utilizing Artificial Intelligence (AI) to support their financial decision-making who took part in this survey. The current section shows and explains the results of the data analysis through various statistical techniques. The findings are illustrated using tables and numerical data, including descriptive analysis.

4.1 Descriptive Analysis

4.1.1 Profile of Respondent Demographics

The personal data of those who participate in this survey is displayed in this part, including their gender, age, highest educational level, employment status, investment experience, and experience with AI in financial market decision-making are all shown in this section. The frequency of each variable will be illustrated using tables and charts. In total, 403 respondents participated in this study, and all of them are investors who use AI to support their investment decision-making.

4.1.1.1 Gender

Table 4.1: *Gender frequency table*

Gender	Frequency	%	Valid %	Cumulative %
Female	206	51.1	51.1	51.1
Male	197	48.9	48.9	100.0
Total	403	100.0	100.0	

Source: Developed for study

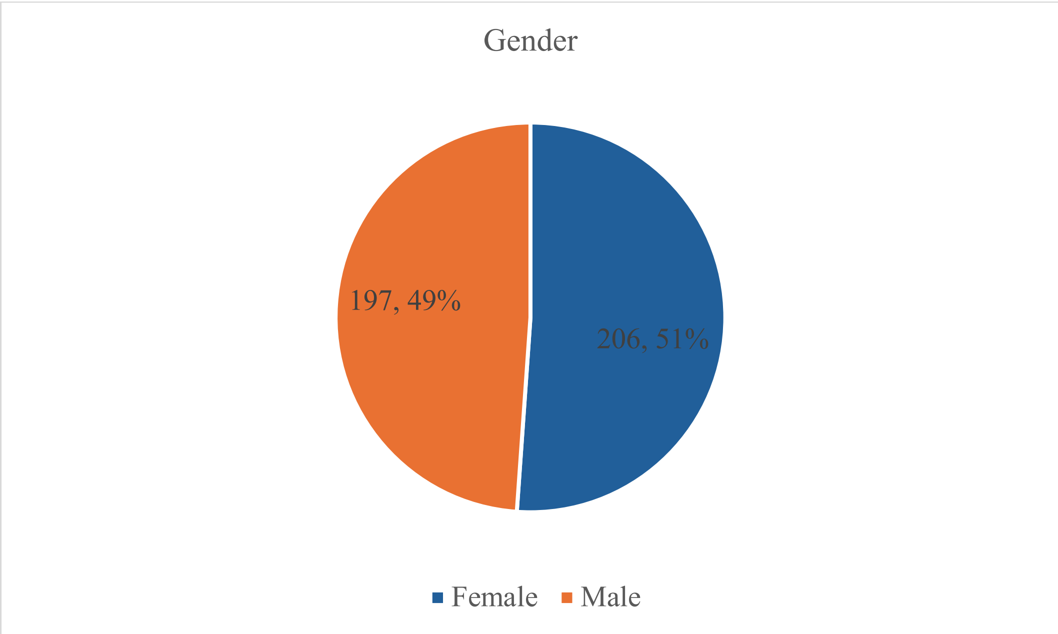


Figure 4.1 Pie Chart for Gender

The allocation of responders by gender is displayed in Table 4.1. There is somewhat higher representation of female participants in this survey, with 206 respondents (51.1%) being female and 197 respondents (48.9%) being male among the 403 participants.

4.1.1.2 Age

Table 4.2: *Age frequency table*

Age	Frequency	%	Valid %	Cumulative %
26-35	194	48.1	48.1	48.1
18-25	103	25.6	25.6	73.7
36-45	70	17.4	17.4	91.1
Above 45	36	8.9	8.9	100.0
Total	403	100.0	100.0	

Source: Developed for study

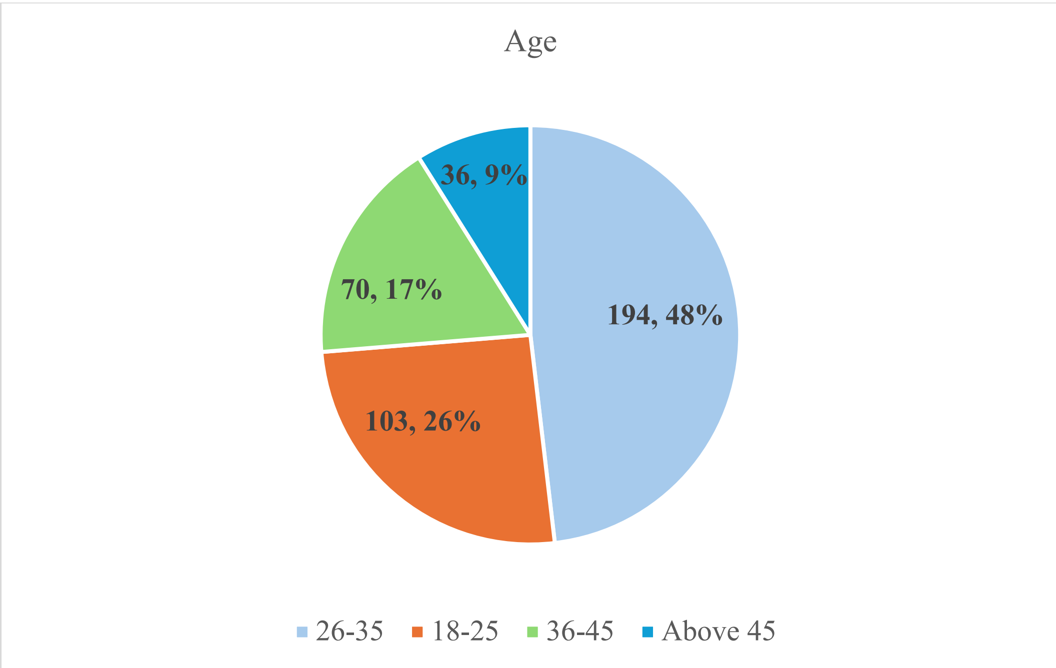


Figure 4.2 Pie Chart for Age

The distribution of the participants by age is seen in Table 4.2. The majority are aged 26–35 years, representing the highest proportion at 48.1%. Respondents aged above 45 years constitute the smallest group, accounting for 8.9% of the whole sample. Meanwhile, 103 respondents (25.6%) are aged 18–25 years, and 70 respondents (17.4%) fall within the 36–45 years age group.

4.1.1.3 Highest Educational Level

Table 4.3: *Highest Educational Level frequency table*

Highest Educational Level	Frequency	%	Valid %	Cumulative %
Bachelor's Degree	216	53.6	53.6	53.6
Diploma	106	26.3	26.3	79.9
SPM	32	7.9	7.9	87.8
Postgraduate Degree	30	7.4	7.4	95.3
STPM	18	4.5	4.5	99.8
UPSR	1	0.2	0.2	100.0
Total	403	100.0	100.0	

Source: Developed for study

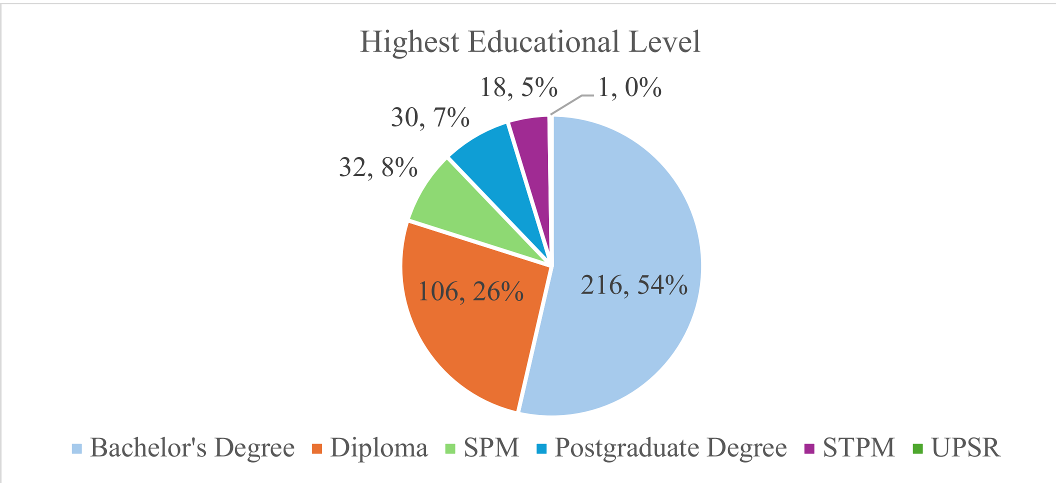


Figure 4.3: Pie Chart for Highest Educational Level

The distribution of respondents according to their highest level of education is shown in Table 4.3. Among the 403 participants, the majority hold a bachelor's degree, with 216 respondents (53.6%) representing the highest proportion among the six education levels. In addition, 106 respondents (26.3%) are diploma holders, 30 respondents (7.4%) have attained a postgraduate degree, 32 respondents (7.9%) are SPM holders, 18 respondents (4.5%) are STPM holders, and 1 respondent (0.2%) has completed UPSR.

4.1.1.4 Employment Status

Table 4.4: *Employment status's frequency table*

Employment Status	Frequency	%	Valid %	Cumulative %
Working (Full-time or Part-time)	228	56.6	56.6	56.6
Self-employed	80	19.9	19.9	76.5
Student	76	18.9	18.9	95.3
Unemployed	13	3.2	3.2	98.5
Retired	6	1.5	1.5	100.0
Total	403	100.0	100.0	

Source: Developed for study

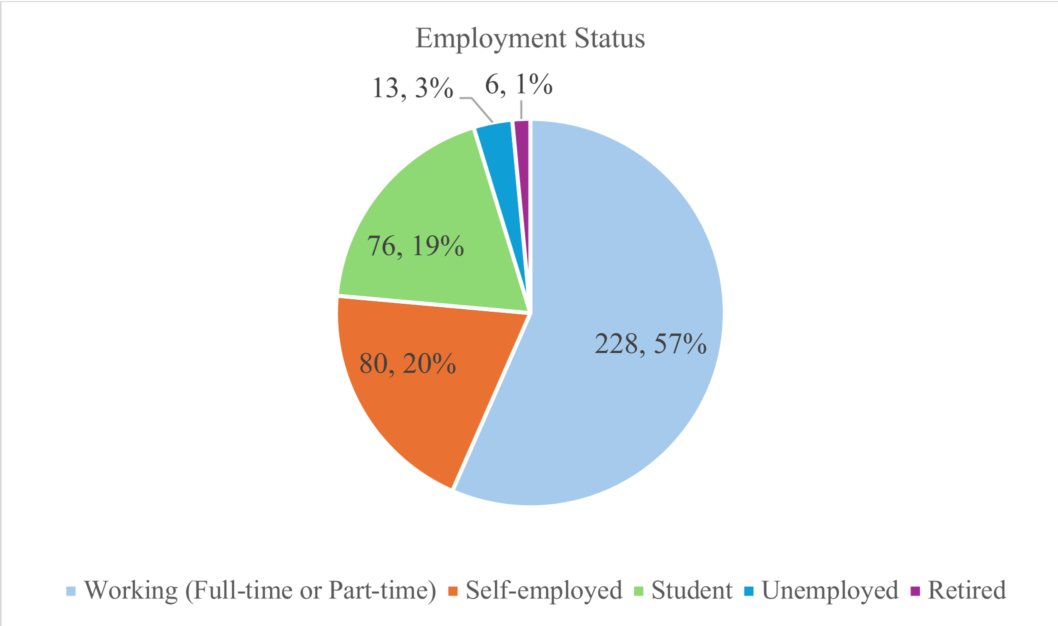


Figure 4.4: Pie Chart for Employment Status

Table 4.4 presents the distribution of surveyed according to their employment status. Among the 403 participants, the majority are employed, either full-time or part-time, comprising 228 respondents (56.6%). In addition, 80 respondents (19.9%) are self-employed, 76 respondents (18.9%) are students, 13 respondents (3.2%) are unemployed, and 6 respondents (1.5%) are retired.

4.1.1.5 Investment Experience

Table 4.5: *Investment Experience frequency table*

Investment Experience	Frequency	%	Valid %	Cumulative %
1-3 years	146	36.2	36.2	36.2
Less than 1 year	121	30.0	30.0	66.2
4-6 years	87	21.6	21.6	87.8
More than 6 years	49	12.2	12.2	100.0
Total	403	100.0	100.0	

Source: Developed for study

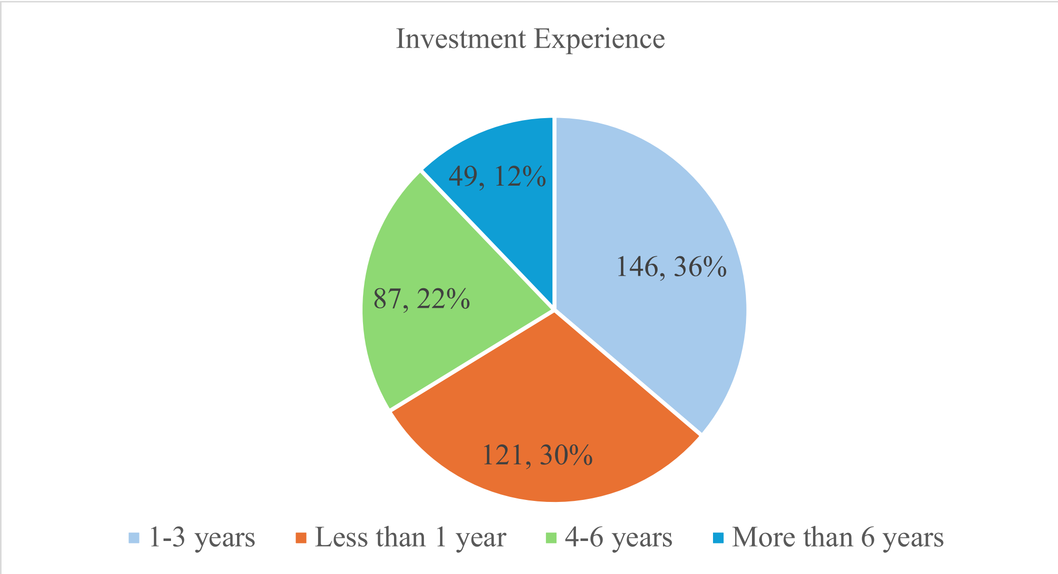


Figure 4.5: Pie Chart for Investment Experience

Table 4.5 presents the distribution of respondents based on their investment experience. Among the 403 participants, the majority have 1–3 years of investment experience. In addition, 121 respondents (30.0%) have less than 1 year of experience, 87 respondents (21.6%) have 4–6 years of experience, and 49 respondents (12.2%) have more than 6 years of investment experience.

4.1.1.6 Experience with AI in Financial Market Decision Making

Table 4.6: *Experience with AI in Financial Market Decision Making frequency table*

Experience with AI in Financial Market Decision Making	Frequency	%	Valid %	Cumulative %
Beginner (just started using AI tools)	193	47.9	47.9	47.9
Intermediate (some experience with AI-driven platforms)	159	39.5	39.5	87.3
Advanced (extensive use of AI in decision-making)	51	12.7	12.7	100.0
Total	403	100.0	100.0	

Source: Developed for study

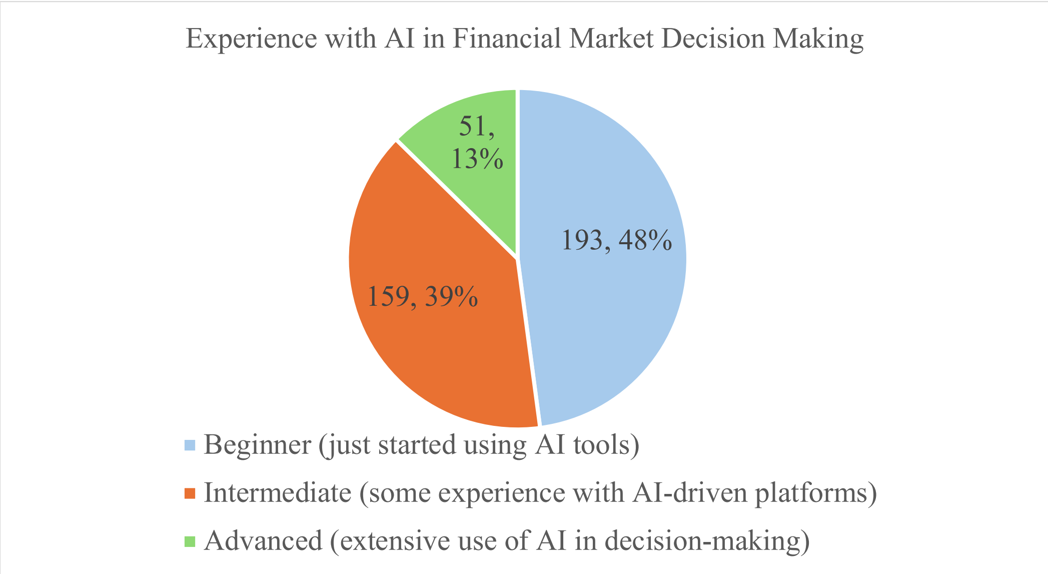


Figure 4.6: Pie Chart for Experience with AI in Financial Market Decision-Making

Table 4.6 illustrates the respondents' experience with AI in financial market decision-making. Among the 403 participants, 193 respondents (47.9%) are classified as beginners, 159 respondents (39.5%) are at an intermediate level, and 51 respondents (12.7%) are advanced users.

4.1.1.7 Monthly Investment Amount in RM

Table 4.7: *Monthly Investment Amount frequency table*

Monthly Investment Amount	Frequency	%	Valid %	Cumulative %
Less than RM1,000	235	58.3	58.3	58.3
RM1,001- RM5,000	137	34.0	34.0	92.3
RM5,001- RM10,000	24	6.0	6.0	98.3
Above RM10,000	7	1.7	1.7	100.0
Total	403	100.0	100.0	

Source: Developed for study

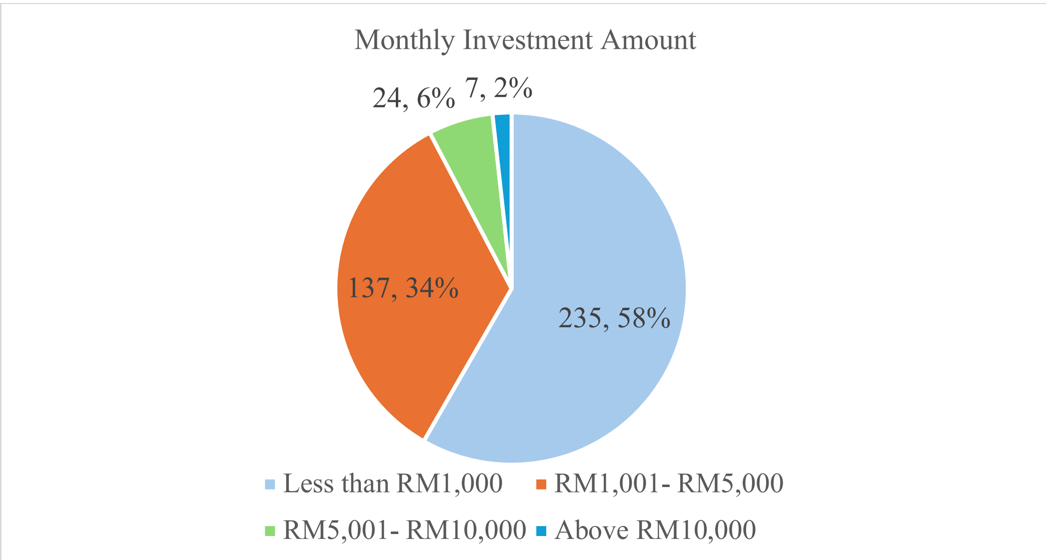


Figure 4.7: Pie Chart for Monthly Investment Amount

Table 4.7 presents the distribution of participants based on their monthly investment amount. Among the 403 participants, the majority (235 respondents, 58.3%) invest below RM1,000 per month. In addition, 137 respondents (34.0%) invest between RM1,001 and RM5,000 per month, 24 respondents (6.0%) invest between RM5,001 and RM10,000, while 7 respondents (1.7%) invest above RM10,000 per month.

4.1.2 Central Tendencies Measurement of Constructs

This part will present the mode, median, standard deviation, and standard deviation for each item within every variable, as well as the overall results with their respective measurements.

Table 4.8: *Mode, median, mean and standard deviation of the variables*

Items	Mean	Median	Mode	Standard Deviation
AI in Financial Market Decision-Making (DV)				
1. The use of AI improves the accuracy of financial market decision-making.	3.92	4.00	4	0.620
2. AI tools help me make faster investment decisions compared to traditional methods.	4.00	4.00	4	0.711
3. AI adoption increases overall efficiency in analyzing financial data.	4.13	4.00	4	0.648
4. I believe AI enhances the quality of predictions in financial market trends.	4.07	4.00	4	0.673

5. The integration of AI contributes to better investment performance outcomes.	4.14	4.00	4	0.660
Reduction in Human Bias (Independent Variable 1)				
1. AI helps to minimize emotional influence in financial investment decisions.	4.20	4.00	4	0.677
2. The use of AI reduces personal judgement errors in financial market analysis.	4.22	4.00	4	0.723
3. AI systems provide more objective investment recommendations compared to human advisors.	4.03	4.00	4	0.819
4. The adoption of AI decreases the likelihood of bias in financial decision-making processes.	4.26	4.00	4	0.732
5. I believe AI reduces reliance on subjective opinions in financial market decisions.	4.38	4.00	5	0.708
Personalized Investment Strategies (Independent Variable 2)				
1. AI-driven financial platforms provide me with investment recommendations that match my personal financial goals.	4.02	4.00	4	0.588
2. I am likely to adopt AI if it offers personalized investment strategies that improve my decision-making performance.	4.11	4.00	4	0.625

3. AI-based investment tools improve my confidence in making investment decisions.	4.00	4.00	4	0.654
4. Personalized recommendations from AI platforms have increased my satisfaction with investment outcomes.	4.07	4.00	4	0.703
5. I believe AI can adapt investment strategies to my changing financial needs over time.	4.28	4.00	4	0.660
Ethical and Regulatory Challenges (Independent Variable 3)				
1. I believe that ethical guidelines are necessary to govern the use of AI in financial market decision-making.	4.21	4.00	4	0.684
2. The lack of clear regulatory frameworks for AI in financial markets reduces transparency and accountability in AI-driven investment decision-making tools.	4.34	4.00	5	0.695
3. I believe financial regulators should enforce transparency and accountability in AI-driven financial tools.	4.36	4.00	5	0.732
4. I believe financial institutions should establish clear ethical guidelines before deploying AI in financial market decision-making.	4.46	5.00	5	0.688
Market Adaptation and Technological Barriers (Independent Variable 4)				

1. The financial market in Malaysia is ready to adopt AI technologies for decision-making.	3.80	4.00	4	0.786
2. The lack of awareness and understanding among market participants hinders AI adoption.	4.16	4.00	4	0.656
3. The slow pace of market adaptation reduces the effectiveness of AI adoption in financial services.	4.19	4.00	4	0.688
4. Integration of AI with existing legacy systems in financial markets is a major challenge.	4.25	4.00	4	0.730
5. A lack of technical expertise among financial professionals is a barrier to adopting AI in financial decision-making.	4.35	4.00	5	0.708
Investor Perception and Trust (Independent Variable 5)				
1. I trust AI systems to provide reliable financial advice.	4.01	4.00	4	0.564
2. I feel comfortable relying on AI for making important investment decision.	3.90	4.00	4	0.697
3. AI adoption in financial markets improves my confidence in financial institutions.	4.07	4.00	4	0.609
4. I trust AI systems to act in my best financial interest without manipulation.	4.20	4.00	4	0.761

5. I perceive AI as a useful tool for analysing complex financial data.	4.40	4.00	5	0.645
Enhanced Market Efficiency and Accuracy (Independent Variable 6)				
1. The use of AI enhances the efficiency of analysing large volumes of financial data.	4.25	4.00	4	0.645
2. AI reduces delays in identifying investment opportunities in the market.	4.04	4.00	4	0.647
3. I believe AI adoption leads to more precise detection of market risks and trends.	4.08	4.00	4	0.631
4. AI contributes to faster and more accurate execution of financial decisions.	4.18	4.00	4	0.677
5. AI helps optimize decision-making by integrating multiple sources of financial data effectively.	4.36	4.00	4	0.664

Source: Developed for study

4.2 Scale Measurement

4.2.1 Reliability Test

In reliability analysis, Cronbach's alpha is a coefficient of internal consistency used to evaluate how closely test items measure the same underlying concept. For the variable ethical and regulatory challenges (ERC), one measurement item (ERC1), which reflects concerns about AI systems making biased or unfair investment decisions, was removed due to its low reliability. The deletion of this item improved the overall reliability of the construct, ensuring that the remaining items more consistently measure the intended concept.

Table 4.9: *Reliability Test Result*

Variable	**Total Items**	**Cronbach's Alpha**
Intention to Adopt AI in Financial Market Decision-Making	5	0.813
Reduction in Human Bias	5	0.815
Personalized Investment Strategies	5	0.785
Ethical and Regulatory Challenges	4	0.855
Market Adaptation and Technological Barriers	5	0.772
Investor Perception and Trust	5	0.783
Enhanced Market Efficiency and Accuracy	5	0.736

Source: Developed for study

The dependent and independent variables in this study showed Cronbach's alpha values between 0.736 and 0.855. Overall, these results indicate acceptable to good reliability, as the values exceed the commonly recommended threshold of 0.70. According to the rule of thumb suggested by Ahmad et al. (2024), Cronbach's alpha values between 0.70 and 0.80 indicate acceptable reliability, whereas values above 0.80 represent good reliability. Therefore, the results imply that the study's questionnaire items are trustworthy and internally consistent, fulfilling the reliability criteria established in earlier studies.

4.2.2 Normality Test

Table 4.10: *Normality Test Result*

Variables	Skewness	Kurtosis
Intention to Adopt AI in Financial Market Decision-Making	-0.733	1.656
Reduction in Human Bias	-0.568	0.508
Personalized Investment Strategies	-1.030	4.391
Ethical and Regulatory Challenges	-0.857	1.223
Market Adaptation and Technological Barriers	-0.810	1.587
Investor Perception and Trust	-1.021	3.628
Enhanced Market Efficiency and Accuracy	-0.786	2.227

Source: Developed for study

Skewness and kurtosis measurements were used to evaluate the data's normality. As shown in Table 4.10, the skewness values for all variables which are Intention to Adopt AI in Financial Market Decision-Making (-0.733), Reduction in Human Bias (-0.568), Personalized Investment Strategies (-1.030), Ethical and Regulatory Challenges (-0.857), Market Adaptation and Technological Barriers (-0.810), Investor Perception and Trust (-1.021), and Enhanced Market Efficiency and Accuracy (-0.786), fall within the acceptable range of -2 to +2. Similarly, all variables' kurtosis values fall within the recommended range of -7 to +7, with Intention to Adopt AI in Financial Market Decision-Making (1.656), Reduction in Human Bias (0.508), Personalized Investment Strategies (4.391), Ethical and Regulatory Challenges (1.223), Market Adaptation and Technological Barriers (1.587), Investor Perception and Trust (3.628), and Enhanced Market Efficiency and Accuracy (2.227). These findings indicates that all of the study's variable are normally distributed, meeting the assumptions required for further statistical analyses.

4.3 Inferential Analysis

4.3.1 Pearson's Correlation Coefficient

Table 4.11: *Pearson Correlation Coefficient Result*

	AI	RHB	PIS	ERC	MATB	IPT	EMEA
AI	1						
RHB	0.561**	1					
PIS	0.585**	0.578**	1				
ERC	0.435**	0.566**	0.432**	1			
MATB	0.473**	0.498**	0.555**	0.485**	1		
IPT	0.503**	0.547**	0.579**	0.381**	0.595**	1	
EMEA	0.534**	0.586**	0.531**	0.480**	0.578**	0.664**	1

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

Table 4.11 presents the Pearson's correlation coefficients among the variables in this study. The results indicate that all independent variables, which are reduction in human bias (RHB), personalized investment strategies (PIS), ethical and regulatory challenges (ERC), market adaptation and technological barriers (MATB), investor perception and trust (IPT), and enhanced market efficiency and accuracy (EMEA), show positive and significant relationships with the adoption of AI in Malaysia's financial market decision-making (AI) at the 0.01 significance level ($p < 0.01$). The correlation coefficients show positive associations, ranging from 0.435 to 0.585.

4.3.2 Multiple Regression Analysis

4.3.2.1 Model Summary

Table 4.12: *Multiple Regression Analysis Result*

R	R^2	Adjusted R^2	Standard Error of the Estimate
0.673	0.453	0.445	0.37335

Source: Developed for study

Table 4.12 represented the result of the multiple regression analysis. The R^2 value is 0.453, indicating that 45.3% of the variance in Intention to Adopt AI in Malaysia's Financial Market Decision-Making is explained by the combined influence of Reduction in Human Bias, Personalized Investment Strategies, Ethical and Regulatory Challenges, Market Adaptation and Technological Barriers, Investor Perception and Trust, and Enhanced Market Efficiency and Accuracy.

4.3.2.2 Coefficients

Table 4.13: *Regression Coefficient*

Variable	**Coefficients Standard Error**	**T-test**	**p-value**
(Constant)	0.200	2.858	0.004***
Reduction in Human Bias	0.048	3.764	<0.001***
Personalized Investment Strategies	0.054	5.689	<0.001***
Ethical and Regulatory Challenges	0.051	1.511	0.132

Market Adaptation and Technological Barriers	0.050	0.910	0.363
Investor Perception and Trust	0.058	1.152	0.250
Enhanced Market Efficiency and Accuracy	0.061	2.843	0.005***

*** significance at 1%, ** significance at 5%, *significance at 10%

The intention to adopt AI in financial market decision-making is strongly influenced by a number of factors, as Table 4.13 shows. The findings indicate that adoption of AI is significantly positively correlated with reduction in human bias ($\beta = 0.048$, $p < 0.001$), personalized investment strategies ($\beta = 0.054$, $p < 0.001$), and enhanced market efficiency and accuracy ($\beta = 0.061$, $p = 0.005$). This implies that the intention to use AI in Malaysia's financial market decision-making is significantly influenced by AI technologies that reduce human bias, offer personalized investment strategies, and enhance market efficiency and accuracy.

However, p-values greater than 0.05 for market adaptation and technological barriers ($p = 0.363$), investor perception and trust ($p = 0.250$), and ethical and regulatory challenges ($p = 0.132$) show that there is no statistically significant relationship between these factors and the adoption of AI in this study.

4.3.2.3 Multicollinearity Test

Table 4.14: *Variance Inflation Factor (VIF) and Tolerance Value*

Independent Variables	Collinearity Statistics	
	Tolerance	VIF
Reduction in Human Bias	0.480	2.082

Personalized Investment Strategies	0.528	1.894
Ethical and Regulatory Challenges	0.610	1.640
Market Adaptation and Technological Barriers	0.515	1.943
Investor Perception and Trust	0.448	2.234
Enhanced Market Efficiency and Accuracy	0.450	2.221

As shown in Table 4.14, the VIF values of the independent variables fall between 1 to 5. Among the independent variables, investor perception and trust has the greatest VIF value of 2.234, while ethical and regulatory challenges have the lowest VIF value of 1.640.

In the event of VIF falls between 1 and 5, independent variables are deemed to be moderately connected; if it is greater than 5, they seem to be highly linked. The higher VIF refers to a higher likelihood of multicollinearity, indicating extensive research is required. A value in excess of 10 in the VIF indicates severe multicollinearity.

In conclusion, this study does not indicate serious multicollinearity issues, as the VIF values among independent variables are all within the commonly accepted threshold, which is between 1 to 5.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATION

5.0 Introduction

The entire study project is included in this chapter. The data from Chapter 4 served as the basis for the decision-making outcomes, which are further examined in this chapter. It offers a thorough explanation and a clear understanding of every variable. In addition, this chapter includes conclusions, recommendations, limitations, and implications.

5.1 Discussion of Major Findings

5.1.1 Drivers of AI adoption in Malaysia's Financial Market Decision-Making

5.1.1.1 Reduction in Human Bias – RHB

The results indicate that reduction in human bias has significant effect on the investors' intention to adopt AI in Malaysia's financial market decision-making. These results are consistent with prior study by Rehman, Dhiman, and Cheema (2024), that found that emotional and cognitive biases can be reduced with the use of AI technologies, such as robo-advisors, which in turn enhanced rationality in investment decisions. Similarly, according to Kavitha et al. (2025), AI algorithms can reduce common behavioural biases like overconfidence, herd mentality, and confirmation bias. Since these biases have been repeatedly demonstrated to have a detrimental impact on financial decision-making (Zahera & Bansal, 2018; Singh et al., 2024; Bakar & Yi, 2016), investors' adoption of AI is strongly supported by its capacity to reduce these biases. In conclusion, previous studies strongly support our study, indicating that reduction in human bias is one of the drivers of AI adoption in Malaysia financial market decision-making.

Hypothesis 1

H_1: There is significant relationship between Reduction in Human Bias and Intention to Adopt AI in Malaysia’s Financial Market Decision-Making

Since the p-value obtained from the multiple linear regression (MLR) analysis for Reduction in Human Bias is less than 0.05 ($p < 0.001$), the null hypothesis (H_0) is rejected.

5.1.1.2 Personalized Investment Strategies – PIS

The results signifies that the independent variable, personalized investment strategies, has significant effect on the investors’ intention to adopt AI in Malaysia’s financial market decision-making. These findings are consistent with previous studies. Firstly, Capponi et al. (2019) suggested that AI-powered models enable integration of client feedback, risk preferences, and behavioral inputs to provide adaptive and personalized investment portfolios that suit the investors’ financial goals. Moreover, study by Fields et al. (2025) found that robo-advisors demonstrate a high level of goal alignment through advanced algorithms, highlighting their ability to provide personalised investment strategies. In addition, Falsetti (2025) also suggested that AI-driven recommendation systems can enhance portfolio performance by tailoring investment decisions based on user-specific data. Thus, previous studies strongly support our study, indicating that personalized investment strategies is one of the drivers of AI adoption in Malaysia financial market decision-making.

Hypothesis 2

H_1: There is significant relationship between PIS and Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Since the p-value obtained from the multiple linear regression (MLR) analysis for Personalized Investment Strategies is less than 0.05 ($p < 0.001$), the null hypothesis (H_0) is rejected.

5.1.1.3 Ethical and Regulatory Challenges – ERC

The findings of this study indicate that ethical and regulatory challenges (ERC) do not have a significant influence on the intention to adopt AI in Malaysia's financial market decision-making. This result differs from previous studies conducted by Deloitte (2025), Challoumis (2024), and Owolabi et al. (2024). Existing literature suggests that while artificial intelligence (AI) enhances efficiency and decision-making in financial markets, it also introduces significant ethical and regulatory concerns. Key issues highlighted in prior research include algorithmic opacity, data bias, and a lack of transparency, which may reduce accountability and trust in AI-driven systems. In addition, the Deloitte (2025) report emphasizes that many financial institutions still lack strong governance frameworks to effectively manage AI-related risks. These challenges are further complicated by regulatory requirements such as the General Data Protection Regulation (GDPR), which requires transparency and accountability in automated decision-making. Overall, previous studies suggest that addressing ethical concerns and strengthening regulatory frameworks are essential to ensure responsible AI adoption in financial decision-making.

However, in the Malaysian context, users may place greater emphasis on the practical performance benefits of artificial intelligence (AI) rather than ethical or regulatory concerns. Research indicates that 79% of Malaysians regularly use AI tools in daily activities, with many reporting that the technology saves time and improves productivity (Stegmann & Goel, 2025). Within Malaysia's banking sector, AI adoption is largely driven by its ability to enhance operational efficiency, improve customer engagement, and strengthen fraud detection systems. Banks use AI for fraud detection, customer analytics, e-KYC, personalized services, and streamlined digital platforms, all of which improve accuracy and speed (Business Today Malaysia, 2025). Furthermore, according to New Straits Times, the Malaysian government is currently developing an Artificial Intelligence (AI) Governance Bill to address accountability, ethical concerns, and risks related to AI use, regulating the entire lifecycle of AI systems and clarifying the responsibilities of developers and implementing organizations. The need for such legislation suggests that AI adoption has progressed faster than the establishment of comprehensive ethical safeguards. Consequently, investors may prioritize functional benefits such as improved accuracy, speed, and efficiency in financial decision-making, rather than focusing on ethical or regulatory concerns (Azmi & Iskandar, 2026). This helps explain why ethical and regulatory challenges were not found to be significant determinants of AI adoption in the Malaysian financial market in this study.

Hypothesis 3

H_0: There is insignificant relationship between ERC and Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Based on the results of the multiple linear regression (MLR) analysis, the p-value for ERC is greater than 0.05 (p = 0.132). Therefore, the null hypothesis (H_0) is not rejected, indicating that ERC has no significant influence on the intention to adopt AI in Malaysia's financial market decision-making.

5.1.1.4 Market Adaptation and Technological Barriers – MATB

The results indicate that market adaptation and technological barriers (MATB) do not have a significant influence on the intention to adopt AI in Malaysia's financial market decision-making. This finding differs from previous studies conducted by Reichard and Rydstrand (2025), Ochuba et al. (2024), and Bhat (2024). Prior research suggests that financial professionals often remain cautious about adopting AI due to issues such as limited model explainability, trust concerns, and difficulties integrating AI systems with legacy infrastructures. Similarly, Ochuba et al. (2024) highlight that technological readiness, data quality, and digital infrastructure play important roles in determining the successful implementation of AI, particularly in emerging economies. Furthermore, Bhat (2024) emphasizes that concerns related to algorithmic transparency, regulatory compliance, and potential systemic risks can further limit widespread AI adoption. Overall, these studies suggest that although AI has strong potential to improve financial decision-making through predictive analytics, automation, and data processing, its adoption may be constrained by various technological and market adaptation barriers.

However, the findings of this study suggest that these barriers may not significantly influence AI adoption within the Malaysian financial market context. The adoption of AI technology in Malaysia has been growing rapidly, especially in the financial sector. Financial bodies in Malaysia are already familiar with AI technology. This reduces the individual users' awareness of technological complexity. The widespread adoption of AI in Malaysia's financial sector indicates institution-level adoption. Consequently, Users benefit from AI through enhanced services, without needing to engage directly with complex systems (Rowena, 2025). Moreover, the fact that 71% of banks and development financial institutions have adopted at least one AI technology shows that the financial sector in Malaysia has a relatively sound technological infrastructure. In addition, Malaysia has one of the highest adoption rates of AI technology in Southeast Asia. Many companies, especially startups, in Malaysia use AI technology more for automation than for transformation (Fintech News Singapore et al., 2026). Furthermore, most users in Malaysia are already familiar with AI technology. Financial bodies and regulatory bodies, such as Bank Negara Malaysia's fintech development programs and regulatory sandbox, also have a significant impact in the development of fintech infrastructure in Malaysia. Due to this, there is a lack of awareness among end users about the complexity of technology and technology infrastructure, as they are mostly handled at the corporate level and not by individual users (Alam, 2021).

Hypothesis 4

H_0: There is insignificant relationship between MATB and Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Since the p-value obtained from the multiple linear regression (MLR) analysis for MATB is greater than 0.05 ($p = 0.363$), the null hypothesis (H_0) is not rejected. This indicates that MATB does not have a significant effect on the intention to adopt AI in Malaysia's financial market decision-making.

5.1.1.5 Investor Perception and Trust – IPT

The results indicate that IPT has no significant effect on the investors' intention to adopt AI in Malaysia's financial market decision-making. These results are not aligned with the prior studies by Cheng et al. (2019), Ting et al. (2023), and Cao et al. (2025). As highlighted by Cheng et al. (2019), trust is influenced by multiple factors such as provider reputation, information quality, service quality, and regulatory support, which suggests that trust does not operate independently. Similarly, Ting et al. (2023) found out that trust varies across different groups of investors, where general investors tend to trust AI more, while financial professionals remain skeptical. In addition, Luo et al. (2024) emphasized that although investors are open to AI adoption, their willingness remains conditional. Therefore, even though trust can encourage adoption as suggested by AlAmayreh et al. (2023), the absence of strong supporting conditions may weaken its direct influence, leading to an insignificant relationship in this study.

According to research, 92% of Malaysian consumers consider fintech services to be reliable and frequently make use of digital financial services. This illustrates the high level of trust in Malaysia. The major factors that contribute to the trust in Malaysia were also revealed to be aspects such as company reputation and brand, data security and regulatory compliance, and government institution support (Business Today Editorial, 2018). Moreover, the increasing trust in digital financial services by the public may also be illustrated by the rapid adoption of digital banking services, which currently reach two million consumers and accumulate billions in deposits (Fintech News Malaysia, 2025). The perception and trust of investors may not have been revealed as a significant factor in our research due to the fact that investors may trust AI-enabled financial services when provided by reputable firms.

Hypothesis 5

H_0: There is insignificant relationship between IPT and Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Since the p-value for IPT is greater than 0.05 (p = 0.250), the null hypothesis (H_0) is not rejected. This indicates that there is no significant relationship between IPT and the intention to adopt AI in Malaysia's financial market decision-making.

5.1.1.6 Enhanced Market Efficiency and Accuracy- EMEA

The results indicate that EMEA has a significant effect on the investors' intention to adopt AI in Malaysia's financial market decision-making. This finding is consistent with prior studies, which show that AI enhances market efficiency and accuracy by processing large volumes of data and improving forecasting performance (Rehman & Bukhari, 2024; Odeyemi et al. 2021; Masood, 2024). In line with Fama's (1970) Efficient Market Hypothesis, AI enables faster information processing and better price reflection. Additionally, AI-driven sentiment analysis allows investors to analyse news and social media efficiently, leading to more informed decisions (Shaikh et al., 2025; Omoseebi et al., 2023). Thus, previous studies strongly support our study, indicating that enhanced market efficiency and accuracy is one of the key drivers of AI adoption in Malaysia's financial market decision-making.

Hypothesis 6

H_1: There is significant relationship between EMEA and Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Since the p-value for EMEA is less than 0.05 (p = 0.005), the null hypothesis (H_0) is rejected. This indicates that there is a significant relationship between EMEA and the intention to adopt AI in financial market decision-making.

5.2 Implication of study

Malaysian investors are increasingly exposed to the use of Artificial Intelligence (AI) in the financial market decision-making. However, there are still many investors facing challenges such as reliance on traditional methods, lack of awareness of the advantages of AI, and limited confidence in AI recommendations. This study examines the intention to adopt AI in Malaysia's financial market decision-making and serves as a useful guideline and reference for policymakers, financial institutions, investors, and future researchers. Based on the findings, reduction in human bias, personalized investment strategies, and enhanced market efficiency and accuracy have a positive relationship with AI adoption. In contrast, ethical regulatory challenges, market adaptation and technological barriers, and investor perception and trust do not have a positively correlate with the desire to adopt AI.

Firstly, this study can provide policymakers with a better understanding of the factors that influence the intention to adopt AI in financial market decision-making. The findings show that factors such as personalized investment strategies, enhanced market efficiency and accuracy that are related to performance based are more significant in influencing the intention to adopt AI. In this way, policymakers can focus on the development and promote high-quality AI technologies in the financial market. Although ethical and regulatory challenges were not significant in this study, policymakers should continue to develop better regulations and policies in order to ensure that AI is implemented in a secure, transparent, and fair manner. Moreover, policymakers can promote and encourage the adoption of AI in the financial market by highlighting its advantages and making it more accessible and easier for users to learn. By doing these, policymakers get to increase investor confidence and reduce uncertainty in using AI in the financial market.

Besides that, this study is also beneficial to financial institutions such as banks and fintech companies. These institutions are able to improve their business strategies and enhance the use of AI in areas such as trading, risk management, and investment advisory services. For example, financial institutions can improve the accuracy and reliability of AI system provided to users and offer personalized investment products in order to meet customers' needs. Additionally, they can encourage more investors to adopt AI in their decision-making process by offering more user-friendly and accessible AI tools.

Furthermore, investors will also get important insights from this study. This study helps investors to understand how AI can improve decision-making in the financial market by reducing human bias and providing effective personalized investment support. In this way, investors could be encouraged to rely more on AI tools when making decisions in the financial market. However, investors should still remain cautious about the potential risks, even though factors such as perception and trust are not significant in this study.

Lastly, this study will provide a foundation for future researchers. By identifying both the significant and non-significant factors influencing the adoption of AI in Malaysia's financial market, future researchers can examine additional variables, contexts, or impacts in order to gain a deeper understanding of AI adoption in the financial market. Moreover, researchers can also examine cross-country comparisons or the impact of regulatory changes over time, thereby contributing to the development of a more comprehensive framework for AI adoption in the financial market decision-making.

5.3 Limitations of Study

The current section outlines a few shortcomings of this study. Firstly, this study employed questionnaires as an instrument to collect primary data, which are the opinions and thoughts of the respondents regarding the factors that influence their intention to adopt AI in financial market decision-making. Questionnaire research is cost-effective and efficient as it enables the questionnaire to reach targeted respondents without geographical limitations (Parajuli, 2004; Patten, 2016).

However, questionnaires are unable to capture deeper insights into the thoughts of the respondents and their reasoning (Patten, 2016). The questions included in the questionnaire may not fully convey the respondents' thoughts on why the factors may influence their intention to adopt AI in Malaysia's financial market decision-making. Consequently, the researchers find it challenging to analyse the respondents' thoughts on the subject matter.

As mentioned earlier, most of the existing studies on AI in the financial market remain conceptual. Hence, there is insufficient empirical validation of social factors within the Malaysian context. As a result, the self-constructed questionnaire items used in this study may not be able to fully capture the key aspects of these factors as some important aspects that can better represent how the factors influence investors' intention to adopt AI in Malaysia financial market decision-making may be excluded by the researchers. This is because this study adopts a purely quantitative approach, that focus on the intentions of investors to adopt AI in financial market decision-making, which may limit the ability to capture subjective perspectives, including personal experiences, emotions, and interpretations. Hence, researchers are unable to investigate investors' behaviour in adopting AI in real life context. Consequently, the findings may lack depth in explaining the underlying reasons and behavioural patterns associated with AI adoption.

Finally, the targeted respondents of this study are limited to individuals who have prior experience using AI in Malaysia financial market decision-making. While this ensures that the responses are more informed, it may limit the generalisability of the findings, as the perspectives of individuals who have not used AI are not included. Therefore, the results may not fully represent the views of the wider population of investors, particularly potential users who may adopt AI in financial market decision making in the future.

5.4 Recommendations for Future Research

This section presents several recommendations for future research. As this study relied solely on questionnaires, future research should consider using qualitative methods such as interviews or a mixed-method approach. This will help capture deeper insights into respondents' thoughts and provide a better understanding of why certain factors influence their intention to adopt AI in financial market decision-making.

In addition, as mentioned earlier, the current study uses self-constructed questionnaire items, future research should incorporate or adapt well-established measurement scales from previous studies. This can help ensure that the variables are more comprehensive and better represent the key aspects influencing AI adoption within investors who invest in Malaysia financial market.

Moreover, this study only focuses on Malaysian individuals who have prior experience in using AI for decision-making in Malaysia financial market. Thus, future research should also include respondents who have not used AI in Malaysia financial market decision-making. This will allow researchers to examine both current users and potential users, providing a more complete understanding of adoption intention across the wider population.

Lastly, as mentioned priorly, there is still limited empirical validation of AI-related factors in the Malaysian financial market, future research should continue to test and validate these factors in the Malaysian context. This will help strengthen existing theories and improve the reliability of findings in this area.

5.5 Summary

This research project aims to analyze the intention to adopt AI in Malaysia's financial market decision-making and its determinants among individuals aged 18 and above who have experience utilizing Artificial Intelligence (AI) to support their financial decision-making. To examine the objectives of this study, several statistical analyses were conducted to ensure the reliability and validity of the results based on the questionnaire data collected. Six determinants were examined in this study, namely reduction in human bias, personalized investment strategies, ethical and regulatory challenges, market adaptation and technological barriers, investor perception and trust, and enhanced market efficiency and accuracy.

Based on the results discussed above, it was found that three out of the six determinants, namely reduction in human bias, personalized investment strategies, and enhanced market efficiency and accuracy, have a significant influence on the dependent variable, which is the intention to adopt AI in Malaysia's financial market decision-making. However, ethical and regulatory challenges, market adaptation and technological barriers, and investor perception and trust were found to have no significant effect on the intention to adopt AI in Malaysia's financial market decision-making.

Nevertheless, the insignificant results do not imply that ethical and regulatory challenges (ERC), market adaptation and technological barriers (MATB), and investor perception and trust (IPT) are not important factors. Instead, these variables may have a weaker influence on individuals' intention to adopt AI in Malaysia's financial market decision-making within the scope of this study.

Despite these insights, this study is subject to several limitations, including the use of a purely quantitative approach, reliance on self-constructed measurement items, and a sample limited to AI-experienced users, which may affect the generalisability and depth of the findings. Therefore, future research is encouraged to adopt mixed-method approaches, incorporate validated measurement scales, and include a broader range of respondents to provide a more comprehensive understanding of AI adoption.

Overall, this study contributes to the existing literature by offering empirical evidence on AI adoption in Malaysia's financial market and provides valuable implications for policymakers, financial institutions, investors, and future researchers.

REFERENCES

Abu-Bader, S. H. (2021). Using statistical methods in social science research: With a complete SPSS guide. Oxford University Press. https://books.google.com.my/books?hl=en&lr=&id=TvYTEAAAQBAJ&oi=fnd&pg =PP1&dq=Abu-Bader

Ahmad, N., Alias, F. A., Hamat, M., & Mohamed, S. A. (2024). Reliability analysis: application of cronbach's alpha in research instruments. *Pioneering the Future: Delving Into E-Learning's Landscape*, 114-119.

Ahmed, S., Alshater, M. M., Ammari, A. E., & Hammami, H., 2022. Artificial intelligence and machine learning in finance: A bibliometric review. Research in International Business and Finance, 61, 101646. https://doi.org/10.1016/j.ribaf.2022.101646

AI and risk management. (2025, April 17). Deloitte. https://www.deloitte.com/global/en/Industries/financial-services/perspectives/gx-ai-and-risk-management.html

Ajayi, V.O. (2023, May). A review on primary sources of data and secondary sources of data. Research Gate. https://www.researchgate.net/publication/370608670_A_Review_on_Primary_Sources_of_Data_and_Secondary_Sources_of_Data

Alam, N. (2021, September 29). Malaysia's Regulatory Framework: A Catalyst for FinTech Adoption. *RESEARCHERS AT ISEAS – YUSOF ISHAK INSTITUTE ANALYSE CURRENT EVENTS*. https://www.iseas.edu.sg/articles-commentaries/iseas-perspective/2021-128-malaysias-regulatory-framework-a-catalyst-for-fintech-adoption-by-nafis-alam/

AlAmayreh, E. M. R., Almajali, D., AlSmadi, L. A., Masadeh, R., Al-Sherideh, A. S., & Majali, S. A. (2023). Antecedents of understanding the investors' acceptance of artificial intelligence: Perceptions from Jordanian context. International Journal of Data and Network Science, 7(4), 1861–1874. https://doi.org/10.5267/j.ijdns.2023.7.006

Aldasoro, I., Gambacorta, L., Korinek, A., Shreeti, V., & Stein, M. (2024, June). Intelligent financial system: How AI is transforming finance (BIS Working Paper No. 1194). Bank for International Settlements. https://www.bis.org/publ/work1194.pdf

Ali, A., & Iskandar, Y. H. P. (2025). The role of artificial intelligence in financial inclusion in emerging markets: A conceptual review. Edelweiss Applied Science and Technology, 9(5), 1303–1323. https://doi.org/10.55214/25768484.v9i5.7157

Alvi, M. H. (2016). *A Manual for Selecting Sampling Techniques in Research.* https://www.researchgate.net/publication/303941309_A_Manual_for_Selecting_Sampling_Techniques_in_Research

Anjana, B. S. (2021). Scales of Measurement in Research. University of Kerala.

Artificial intelligence in the Malaysian financial sector. (2025). In *https://www.bnm.gov.my/-/dp-aifs25*. Bank Negara Malaysia.

Asenahabi, B. M. (2019). Basics of research design: A guide to selecting appropriate research design. *International Journal of Contemporary Applied Researches*, *6*(5), 76-89.

Ashta, A., & Herrmann, H. (2021). Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance. Strategic Change, 30(3), 211–222. https://doi.org/10.1002/jsc.2404

Ashurov, S., & Azman, M. N. (2025, March 28). *MALAYSIA'S AI REVOLUTION IN ISLAMIC FINANCE: a REGIONAL AND GLOBAL AMBITION*. BERNAMA. https://www.bernama.com/en/thoughts/news.php?id=2406061

Ayoub, A., & Balawi, A. (2022). Herd behavior and its effect on the stock market: An economic perspective. *Quality – Access to Success*, *23*(188), 285–289. https://doi.org/10.47750/QAS/23.188.38

Azhar, D. (2024, October 2). *Oracle to invest $6.5 billion to set up cloud facilities in Malaysia*. Reuters. https://www.reuters.com/technology/oracle-invest-65-billion-set-up-cloud-facilities-malaysia-2024-10-02

Azmi, A., & Iskandar, I. M. (2026, February 24). PM: AI Governance Bill to tackle accountability and ethics in AI use. *NST Online*. https://www.nst.com.my/news/nation/2026/02/1384142/pm-ai-governance-bill-tackle-accountability-and-ethics-ai-use

Bai, X., Zhuang, S., Xie, H., & Guo, L. (2024, July 1). Leveraging generative artificial intelligence for financial market trading data management and prediction [Preprint]. Preprints.org. https://doi.org/10.20944/preprints202407.0084.v1

Bakar, S., & Yi, A. N. C. (2016). The impact of psychological factors on investors' decision making in Malaysian stock market: A case of Klang Valley and Pahang. *Procedia Economics and Finance*, *35*, 319–328. https://doi.org/10.1016/s2212-5671(16)00040-x

Bank of International Settlement. (2022). Globalisation and the operation of monetary policy in Malaysia. Retrieved from https://www.bis.org/publ/bppdf/bispap23q.pdf

Bhandari, P. (2023, June 22). What is quantitative research? | Definition, uses & methods. Scribbr. https://www.scribbr.com/methodology/quantitative-research/

Bhat, N. a. K. (2024). Application and impact of artificial intelligence in financial decision making. International Journal of Scientific Research in Science Engineering and Technology, 11(5), 57–63. https://doi.org/10.32628/ijsrset2411417

Bhattacherjee, A. (2012). Social science research: Principles, methods, and practices (2nd ed.). University of South Florida.

BNM. (2006). Overview of the Financial System. Retrieved from https://www.bnm.gov.my/documents/20124/856401/cp01.pdf/ff4c04af-d4bf-9681-1d32-03c7625c1620?t=1585799594572

BNM. (2023, 13 April). The Malaysian Islamic Financial Market Report. Retrieved from https://www.bnm.gov.my/documents/20124/54166/The-Malaysian-Islamic-Financial-Market-Report.pdf

Bursa. (2025). Corporate History. Retrieved from https://www.bursamalaysia.com/about_bursa/about_us/corporate_history

Business Today Editorial. (2025, April 4). Building Trustworthy AI In Malaysian Banking: Overcoming Data, Compliance and Talent Challenges. *Business Today*. https://www.businesstoday.com.my/2025/04/04/building-trustworthy-ai-in-malaysian-banking-overcoming-data-compliance-and-talent-challenges

Caduff, C., & Ranganathan, P. (2023). Designing and validating a research questionnaire - Part 1. *Perspectives in Clinical Research*, *14*(3), 152–155. https://doi.org/10.4103/picr.picr_140_23

Cao, X., De Zwaan, L., & Wong, V. (2025). Building trust in roboadvisory: technology, firm-specific and system trust. *Qualitative Research in Financial Markets.* https://doi.org/10.1108/qrfm-02-2024-0033

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2019, November 4). *Personalized Robo-Advising: Enhancing Investment through Client Interaction*. arXiv.org. https://arxiv.org/abs/1911.01391

CEIC. (2025). Malaysia Market Capitalization. Retrieved from https://www.ceicdata.com/en/indicator/malaysia/market-capitalization

Chakra, S., Dey, S., John, A., & Kanti, S. (2024, December 16). *The Human Factor in AI Decision-Making: Mitigating bias and error*.

Chakrabarty, B., Hendershott, T., Nawn, S., & Pascual, R. (2017). Order exposure in high frequency markets. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3074049

Challoumis, C. (2024, November 15). WHAT ARE THE ETHICAL IMPLICATIONS OF AI IN FINANCIAL SYSTEMS? XVII International Scientific Conference. Dortmund. Germany. 07-08.11.2024. https://www.researchgate.net/publication/385858783

Cheng, X., Guo, F., Chen, J., Li, K., Zhang, Y., & Gao, P. (2019). Exploring the trust influencing mechanism of Robo-Advisor Service: a mixed method approach. Sustainability, 11(18), 4917. https://doi.org/10.3390/su11184917

CliffsNotes. (2024, March 16). What is the scale (of measurement). https://www.cliffsnotes.com/study-notes/5657532

Department of Statistics Malaysia. (2025, July 31). *Current population estimates, Malaysia, 2025*. Current Population Estimates 2025

Dibekulu, D. (2020). An overview of data analysis and interpretations in research. *ResearchGate*. https://doi.org/10.14662/IJARER2020.015

Dikko, M. (2016). Establishing construct validity and reliability: Pilot testing of a qualitative interview for research in Takaful (Islamic insurance). The qualitative report, 21(3), 521-528.

EY. (2021, February 8).*Updated: Participating in digital banking, Malaysia*. https://www.ey.com/en_my/technical/take-5-business-alert/updated-participating-indigital-banking-malaysia

Falsetti, Giovanni. "The Impact of AI-Driven Robo-Advisors on Decision-Making Process and Personalization of Investors - University of Twente Student Theses." Utwente.nl, vol. 42, 31 Jan. 2025, essay.utwente.nl/105120/, https://purl.utwente.nl/essays/105120.

Fama, E. F. (1970). Efficient Capital Markets: A review of theory and Empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fields, Gery, et al. "Personalized Financial Advisory through AI: Evaluating the Efficacy of Robo-Advisors and Machine Learning in Tailored Investment Strategies." ResearchGate, 3 Apr. 2025, www.researchgate.net/publication/390450091_Personalized_Financial_Advisory_Through_AI_Evaluating_the_Efficacy_of_Robo-Advisors_and_Machine_Learning_in_Tailored_Investment_Strategies.

Fintech News Malaysia. (2025, December 3). *Digital banks in Malaysia hold RM3.1 billion in deposits, serve nearly 2 million users*. Fintech News Malaysia. https://fintechnews.my/55663/digital-banking-news-malaysia/malaysia-digital-banks/

Fintech News Singapore, Fintech News Singapore, & Fintech News Singapore. (2026, March 10). *AI adoption surges in Southeast Asia; Singapore leads but Malaysia shows faster growth*. Fintech Singapore. https://fintechnews.sg/122832/ai/ai-adoption-surges-in-southeast-asia-singapore-leads-but-malaysia-shows-faster-growth

Fletcher, G. G. S., & Le, M. M. (2021). The future of AI accountability in the financial markets. Vand. J. Ent. & Tech. L., 24, 289.

Gani, A., Imtiaz, N., Rathakrishnan, M., & Krishnasamy, H. N. (2020). A pilot test for establishing validity and reliability of qualitative interview in the blended learning English proficiency course. Journal of critical reviews, 7(05), 140-143.

Ghanad, A. (2023). An overview of quantitative research methods. *International journal of multidisciplinary research and analysis*, *6*(08), 3794-3803.

Grandison, T., and Sloman, M. (2009). A survey of trust in internet applications. *IEEE Communications Surveys & Tutorials, vol. 3, no. 4, pp. 2-16, Fourth Quarter 2000.* doi: 10.1109/COMST.2000.5340804.

Grežo, M. (2020). Overconfidence and financial decision-making: a meta-analysis. *Review of Behavioral Finance*, *13*(3), 276–296. https://doi.org/10.1108/rbf-01-2020-0020

Gupta, A., & Gupta, N. (2023). *Research methodology*. SBPD Publications. https://books.google.com.my/books?id=PzSYEAAAQBAJ

Gupta, A., Puri, M., Keshan, M., & Tiwari, V. (2024, July 15). *AI in financial decision-making: Revolutionizing investment strategies and risk management*. Paper presented at the Global Forum for Financial Consumers (GFFC 2024), Cornell University. SSRN. https://doi.org/10.2139/ssrn.5085764

Hayes, A. (2024, June 27). *Descriptive Statistics: definition, overview, types, and examples*. Investopedia. https://www.investopedia.com/terms/d/descriptive_statistics.asp

Hilton, D. J. (2001). The Psychology of Financial Decision-Making: Applications to Trading, Dealing, and Investment Analysis. *Journal of Psychology and Financial Markets*, *2*(1), 37–53. https://doi.org/10.1207/S15327760JPFM0201_4

Hong, H. (2025, August 19). *Bank Negara Malaysia's Discussion Paper – Artificial Intelligence in the Malaysian Financial Sector - HHQ*. HHQ -. https://hhq.com.my/posts/bank-negara-malaysias-discussion-paper-artificial-intelligence-in-the-malaysian-financial-sector

Imasuen, K. (2022). Sample size determination in test-retest and Cronbach alpha reliability estimates. *British Journal of Contemporary Education, 2*(1), 17–29. https://doi.org/10.52589/BJCEFY266HK9

Investopedia. (n.d.). *Money laundering risk (MLR).* Investopedia. https://www.investopedia.com/terms/m/mlr.asp

Investopedia. (n.d.). *Multicollinearity.* Investopedia. https://www.investopedia.com/terms/m/multicollinearity.asp

Kahneman, D., & Riepe, M. W. (1998). Aspects of investor psychology. *Journal of portfolio management*, *24*(4), 52-+.

Kavitha, D. M., Hanumanthu, D. K. D., Sai, O. N., Chandrashekhar, G. & Sugandha, D. S. (2025). The Role of Artificial Intelligence in Financial Decision-Making. *Journal of Marketing & Social Research, 2*(2), 189-198.

Kim, H. Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. Restorative dentistry & endodontics, 38(1), 52 54.

Krejcie, R., & Morgan, D. (1970). Determining sample size for research activities. Educational and psychological measurement, 30(3), 607-610.

Luo, H., Liu, X., Lv, X., Hu, Y., & Ahmad, A. J. (2024). Investors' willingness to use robo-advisors: Extrapolating influencing factors based on the fiduciary duty of investment advisors. International Review of Economics & Finance, 94, 103411. https://doi.org/10.1016/j.iref.2024.103411

Maple, C., Szpruch, L., Epiphaniou, G., Staykova, K., Singh, S., Penwarden, W., Wen, Y., Wang, Z., Hariharan, J., & Avramovic, P. (2023, August 31). The AI revolution: Opportunities and challenges for the finance sector (arXiv preprint arXiv:2308.16538). arXiv. https://doi.org/10.48550/arXiv.2308.16538

Marshall, G. (2005). The purpose, design and administration of a questionnaire for data collection. *Radiography, 11*(2), 131–136. https://doi.org/10.1016/j.radi.2004.09.002

Masood, F. (2024). Impact of artificial intelligence on financial markets. *International Journal of Emerging Multidisciplinaries: Social Science, 3*(1), 8. https://doi.org/10.54938/ijemdss.2024.03.1.359

Mat Roni, S., & Djajadikerta, H. G. (2021). *Data analysis with SPSS for survey-based research*. Springer Singapore. https://doi.org/10.1007/978-981-16-0193-

Mazhar, S.A. (2021). Methods of data collection: a fundamental tool of research. *Journal of Integrated Community Health, 10* (01), 6-10. https://doi.org/10.24321/2319.9113.202101

Milana, C., & Ashta, A. (2021). Artificial intelligence techniques in finance and financial markets: A survey of the literature. https://doi.org/10.1002/jsc.2404

MyGOV - the government of Malaysia's official portal.(n.d.). https://www.malaysia.gov.my/portal/content/31012

Nahar, J., Nishat, N., Shoaib, A. S. M., & Hossain, Q. (2024). Market efficiency and stability in the era of high-frequency trading: A comprehensive review. *International Journal of Business and Economics, 1*(3), 1–13. https://doi.org/10.62304/ijbm.v1i3.166

Newly announced digital banks to benefit from pandemic-driven digitalisation; immediate threat to traditional banks moderated by regulatory threshold. (2022, April 29). Ram Rating. https://www.ram.com.my/pressrelease/?prviewid=5977

Nor, N. I. M. (2024). Key trends driving adoption of generative artificial intelligence in Malaysian banking sectors. *Technology and Investment*, *15*(01), 77–89. https://doi.org/10.4236/ti.2024.151005

Ochuba, N. N. A., Adewumi, N. A., & Olutimehin, N. D. O. (2024). THE ROLE OF AI IN FINANCIAL MARKET DEVELOPMENT: ENHANCING EFFICIENCY AND ACCESSIBILITY IN EMERGING ECONOMIES. Finance & Accounting Research Journal, 6(3), 421–436. https://doi.org/10.51594/farj.v6i3.969

Odeyemi, A., Falaiye, T., Ogunleye, T., & Oyeleke, A. (2024). Odeyemi, A., Falaiye, T., Ogunleye, T., & Oyeleke, A. (2024). Machine learning in financial forecasting: A U.S. review—Exploring the advancements, challenges, and implications of AI-driven predictions in financial markets. *World Journal of Advanced Research and Reviews, 21*(2), 1969–1984. https://doi.org/10.30574/wjarr.2024.21.2.0377

Olatokun, W. M., & Igbinedion, L. J. (2009, January). The adoption of Automatic Teller Machines in Nigeria: An application of the Theory of Diffusion of Innovation. In E. Cohen (Ed.), InSITE 2009: Informing Science + IT Education Conference, Volume 6 (pp. 373–393). Informing Science Institute. https://doi.org/10.28945/3332

Omoseebi, A., Owen, J., & Loveth, Q. (2023, November). *Natural language processing (NLP) for sentiment analysis in financial markets*. ResearchGate. https://www.researchgate.net/publication/388848099_Natural_language_processing_NLP_for_sentiment_analysis_in_financial_markets

Ong, M. H. A., & Puteh, F. (2017). Quantitative data analysis: Choosing between SPSS, PLS, and AMOS in social science research. *International Interdisciplinary Journal of Scientific Research*, *3*(1), 14-25.

Owolabi, O. S., Uche, P. C., Adeniken, N. T., Ihejirika, C., Islam, R. B., & Chhetri, B. J. T. (2024). Ethical implication of artificial intelligence (AI) adoption in financial decision making. Computer and Information Science, 17(1), 49. https://doi.org/10.5539/cis.v17n1p49

Parajuli, B. K. (2004). Questionnaire: A tool of primary data collection. *Himalayan Journal of Sociology and Anthropology*, *1*, 51-63.

Patten, M. L. (2016). *Questionnaire research: A practical guide* (4th ed.). Routledge.

PESTLEanalysis Team. (2020). Descriptive analysis: How-To, Types, Examples. PESTLE Analysis. https://pestleanalysis.com/descriptive-analysis/

Pillai, V. (2023). Integrating AI-Driven techniques in Big Data Analytics: Enhancing Decision-Making in financial markets. International Journal of Engineering and Computer Science, 12(07), 25774–25788. https://doi.org/10.18535/ijecs/v12i07.4745

Rahayu, N. I., Muktiarni, M., & Hidayat, Y. (2024). *An Application of Statistical Testing: A guide to basic parametric statistics in educational research using SPSS*. https://ejournal.kjpupi.id/index.php/ajse/article/view/438

Rai, N., & Thapa, B. (2015). A study on purposive sampling method in research. *Kathmandu: Kathmandu School of Law*, *5*(1), 8-15.

Ranganathan, P., & Caduff, C. (2023). Designing and validating a research questionnaire - Part 1. *Perspectives in Clinical Research*, *14*(3), 152–155. https://doi.org/10.4103/picr.picr_140_23

Ranjan, R. (2024). THE EVOLUTION OF DIGITAL BANKING: IMPACTS ON TRADITIONAL FINANCIAL INSTITUTIONS. International Journal of Progressive Research in Engineering Management and Science 04(09), 753-763.

Rehman, M., Dhiman, D. B., & Cheema, G. S. (2024). Minds and Machines: Impact of Emotional Intelligence on Investment Decisions with Mediating the Role of Artificial Intelligence. *International Journal of Engineering, Business and Management*, *8*(1), 01-10 https://dx.doi.org/10.22161/ijebm.8.1.1

Roni, S. M., & Djajadikerta, H. G. (2021). Data Analysis with SPSS for Survey-based Research. In *Springer eBooks*. https://doi.org/10.1007/978-981-16-0193-4

Rowena, A. (2025, August 19). *6 out of 10 financial firms are betting on AI as BNM moves to guide adoption*. Fintech News Malaysia. https://fintechnews.my/53546/ai/ai-adoption-malaysia-financial-sector

Rydstrand, J., & Reichard, S. (2025). AI in Investment Decision-Making : Navigating the Use Cases, Perception and Adoption Barriers in Finance. DIVA. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1979065&dswid=-2124

Salkind, N. (2010). *Encyclopedia of Research Design*. https://doi.org/10.4135/9781412961288

Sam-Bulya, N. J., Omokhoa, H. E., Ewim, C. P. M., & Achumie, G. O. (2021). Developing a framework for Artificial Intelligence-Driven financial inclusion in emerging markets. *International Journal of Multidisciplinary Research and Growth Evaluation*, *2*(1), 677–692. https://doi.org/10.54660/.ijmrge.2021.2.1.677-692

Schoonenboom, J. (2023). The fundamental difference between qualitative and quantitative data in mixed methods research. In Forum Qualitative

Sozialforschung/Forum: Qualitative Social Research (Vol. 24, No. 1). https://doi.org/10.17169/fqs-24.1.3986

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). Wiley.

Shaikh, S. Z., Khan, K., Sherwani, F. K., & Khan, M. U. (2025). Smart trading: Unlocking artificial intelligence in the stock market. *The Business & Management Review, 15*(3). https://doi.org/10.24052/BMR/V15NU03/ART-17

Shrestha, N. (2020). Detecting multicollinearity in regression analysis. *American journal of applied mathematics and statistics*, *8*(2), 39-42.

Shukla, S., & Shukla, S. K. (2025). Exploring the Impact of Cognitive Biases on StockInvestment Choices: A Scale DevelopmentPerspective. *European Journal of Business Management and Research*, *10*(4), 28–34. https://doi.org/10.24018/ejbmr.2025.10.4.2749

Simkus, J. (2023). Pilot study in research: Definition & examples. Simply Psychology. https://www.simplypsychology.org/pilot-studies.html#Questionnaire-Pilot-Study

Singh, D., Malik, G., Jain, P., & Abouraia, M. (2024). A systematic review and research agenda on the causes and consequences of financial overconfidence. *Cogent Economics & Finance*, *12*(1). https://doi.org/10.1080/23322039.2024.2348543

Sizan, M. M. H., Das, B. C., Shawon, R. E. R., Rana, M. S., Al Montaser, M. A., Chouksey, A., & Pant, L. (2023). AI-enhanced stock market prediction: Evaluating machine learning models for financial forecasting in the USA. *Journal of Business and Management Studies, 5*(4), 152–166. https://doi.org/10.32996/jbms.2023.5.4.16

Source, M. (2024, May 2). *Microsoft announces US$2.2 billion investment to fuel Malaysia's cloud and AI transformation - Microsoft Stories Asia*. Microsoft Stories Asia. https://news.microsoft.com/apac/2024/05/02/microsoft-announces-us2-2-billion-investment-to-fuel-malaysias-cloud-and-ai-transformation/

Stegmann, H., & Goel, S. (2025, December 8). AI ADOPTION IN MALAYSIA: TRANSFORMING OPTIMISM INTO VALUE. *The Star*. https://www.thestar.com.my/news/nation/2025/12/08/ai-adoption-in-malaysia-transforming-optimism-into-value

Stewart, & Ken. (2026, February 13). *Pearson's correlation coefficient | Definition, Formula, & Facts*. Encyclopedia Britannica. https://www.britannica.com/topic/Pearsons-correlation-coefficient

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International journal of medical education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Team, I. (2025, July 23). *Variance Inflation Factor (VIF): Definition and Formula*. Investopedia. https://www.investopedia.com/terms/v/variance-inflation-factor.asp

Ting, H., Hsu, W., & Lee, M. (2023). AI in Finance: Shaping Investor Behavior and Trust through Equity Research Report. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4667165

Turney, S. (2024, February 10). Pearson Correlation Coefficient (r) | Guide & Examples. Scribbr. https://www.scribbr.com/statistics/pearson-correlation-coefficient/

Van Teijlingen, E., & Hundley, V. (2001). The importance of pilot studies. Social research update, (35), 1-4.

Yacoub, A. D., Slim, S. O., & Aboutabl, A. E. (2024). A survey of sentiment analysis and sarcasm detection: Challenges, techniques, and trends. *International Journal of Electrical and Computer Engineering Systems, 15*(1), 69–78. https://doi.org/10.32985/ijeces.15.1.7

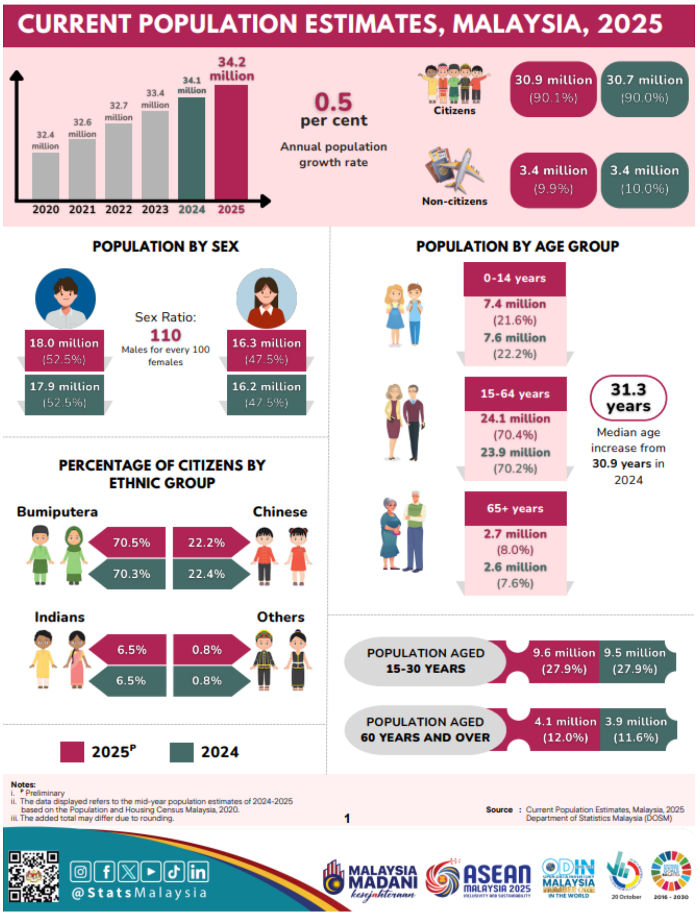
Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets, 10*(2), 210–251. https://doi.org/10.1108/QRFM-04-2017-0028

Zahid, A. Z. M. (2024, July 16). *Adnan Zaylani Mohamad Zahid: Banking in the era of generative AI*. https://www.bis.org/review/r240716g.htm

APPENDICES

Appendix 3.1: Estimated Population of Malaysia in 2025

Source: Department of Statistics Malaysia (2025)



Appendix 3.2: Table for Determining Sample Size from a Given Population

Source: Krejcie & Morgan, 1970

TABLE 1
Table for Determining Sample Size from a Given Population

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size.
S is sample size.

Appendix 3.3: Self-Constructed Questionnaire

Acknowledgement of Notice

( ) I have been notified and that I hereby understood, consented and agreed per UTAR above notice

( ) I disagree, my personal data will not be processed

Section A: Demographic Questions

Age

( ) 18-25

( ) 26-35

( ) 36-45

( ) Above 45

Gender

( ) Male

( ) Female

Highest Education Level

( ) SPM

( ) STPM

( ) Diploma

( ) Bachelor's Degree

( ) Master's Degree

( ) Doctorate (PhD)

( ) Other

Employment Status

( ) Student

( ) Employed (Full time/ Part-time)

( ) Self-employed

( ) Unemployed

( ) Retired

Investment Experience

( ) Less than 1 year

( ) 1-3 years

( ) 4-6 years

( ) More than 6 years

Familiarity with AI in Financial Market Decision-Making

( ) Beginner (just started using AI tools)

( ) Intermediate (some experience with AI-driven platforms)

( ) Advanced (extensive use of AI in decision-making)

Monthly Investment Amount (in RM)

( ) Below RM1,000

( ) RM1,001 – RM5,000

( ) RM5,001 – RM10,000

( ) Above RM10,000

Section B: AI in Financial Market Decision- Making

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The use of AI improves the accuracy of financial market decision-making.	1	2	3	4	5
AI tools help me make faster investment decisions compared to traditional methods.	1	2	3	4	5
AI adoption increases overall efficiency in analyzing financial data.	1	2	3	4	5
I believe AI enhances the quality of predictions in financial market trends.	1	2	3	4	5
The integration of AI contributes to better investment performance outcomes.	1	2	3	4	5

Section C: Reduction in Human Bias

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI helps to minimize emotional influence in financial investment decisions.	1	2	3	4	5
The use of AI reduces personal judgement errors in financial market analysis.	1	2	3	4	5
AI systems provide more objective investment recommendations compared to human advisors.	1	2	3	4	5
The adoption of AI decreases the likelihood of bias in financial decision-making processes.	1	2	3	4	5
I believe AI reduces reliance on subjective opinions in financial market decisions.	1	2	3	4	5

Section D: Personalised Investment Strategies

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI-driven financial platforms provide me with investment	1	2	3	4	5

recommendations that match my personal financial goals.					
I am likely to adopt AI if it offers personalized investment strategies that improve my decision-making performance.	1	2	3	4	5
AI-based investment tools improve my confidence in making investment decisions.	1	2	3	4	5
Personalized recommendations from AI platforms have increased my satisfaction with investment outcomes.	1	2	3	4	5
I believe AI can adapt investment strategies to my changing financial needs over time.	1	2	3	4	5

Section E: Ethical and Regulatory Challenges

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am concerned that AI systems in finance may make biased or unfair investment decisions.	1	2	3	4	5

I believe that ethical guidelines are necessary to govern the use of AI in financial market decision-making.	1	2	3	4	5
The lack of clear regulatory frameworks for AI in financial markets reduces transparency and accountability in AI-driven investment decision-making tools.	1	2	3	4	5
I believe financial regulators should enforce transparency and accountability in AI-driven financial tools.	1	2	3	4	5
I believe financial institutions should establish clear ethical guidelines before deploying AI in financial market decision-making.	1	2	3	4	5

Section F: Market Adaptation and Technological Barriers

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

The financial market in Malaysia is ready to adopt AI technologies for decision-making.	1	2	3	4	5
The lack of awareness and understanding among market participants hinders AI adoption.	1	2	3	4	5
The slow pace of market adaptation reduces the effectiveness of AI adoption in financial services.	1	2	3	4	5
Integration of AI with existing legacy systems in financial markets is a major challenge.	1	2	3	4	5
A lack of technical expertise among financial professionals is a barrier to adopting AI in financial decision-making.	1	2	3	4	5

Section G: Investor Perception and Trust

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

I trust AI systems to provide reliable financial advice.	1	2	3	4	5
I feel comfortable relying on AI for making important investment decision.	1	2	3	4	5
AI adoption in financial markets improves my confidence in financial institutions.	1	2	3	4	5
I trust AI systems to act in my best financial interest without manipulation.	1	2	3	4	5
I perceive AI as a useful tool for analysing complex financial data.	1	2	3	4	5

Section H: Enhanced Market Efficiency and Accuracy

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The use of AI enhances the efficiency of analysing large volumes of financial data.	1	2	3	4	5
AI reduces delays in identifying investment	1	2	3	4	5

opportunities in the market.					
I believe AI adoption leads to more precise detection of market risks and trends.	1	2	3	4	5
AI contributes to faster and more accurate execution of financial decisions.	1	2	3	4	5
AI helps optimize decision-making by integrating multiple sources of financial data effectively.	1	2	3	4	5

Appendix 3.4: Pilot Test

DV: Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Reliability Statistics

Cronbach's Alpha	N of Items
.876	5

IV1: Reduction in Human Bias

Reliability Statistics

Cronbach's Alpha	N of Items
.920	5

IV2: Personalized Investment Strategies

Reliability Statistics

Cronbach's Alpha	N of Items
.876	5

IV3: Ethical and Regulatory Challenges

Reliability Statistics

Cronbach's Alpha	N of Items
.858	5

IV4: Market Adaptation and Technological Barriers

Reliability Statistics

Cronbach's Alpha	N of Items
.864	5

IV5: Investor Perception and Trust

Reliability Statistics

Cronbach's Alpha	N of Items
.928	5

IV6: Enhanced Market Efficiency and Accuracy

Reliability Statistics

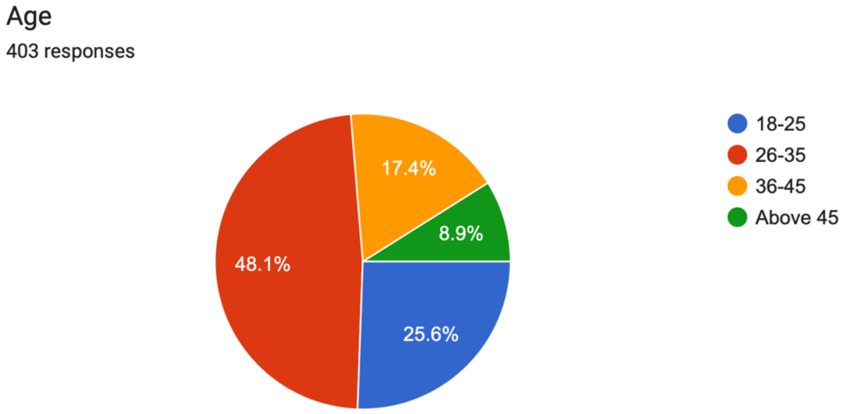
Cronbach's Alpha	N of Items
.907	5

Appendix 4.1: Descriptive Analysis

Age

Age

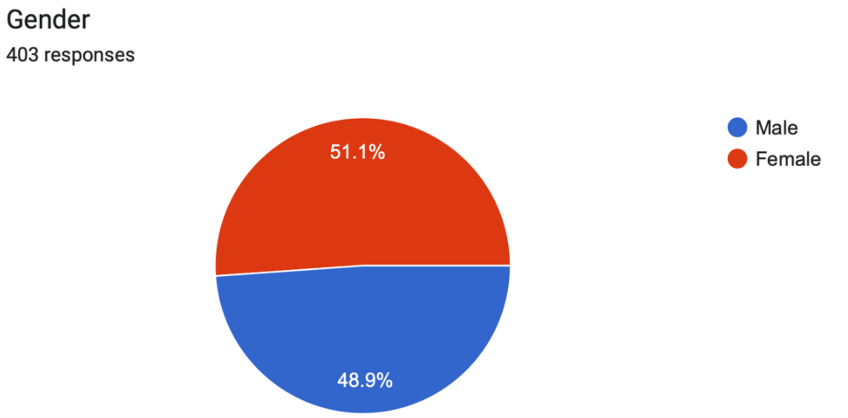
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25	103	25.6	25.6	25.6
	26-35	194	48.1	48.1	73.7
	36-45	70	17.4	17.4	91.1
	Above 45	36	8.9	8.9	100.0
	Total	403	100.0	100.0	



Gender

Gender

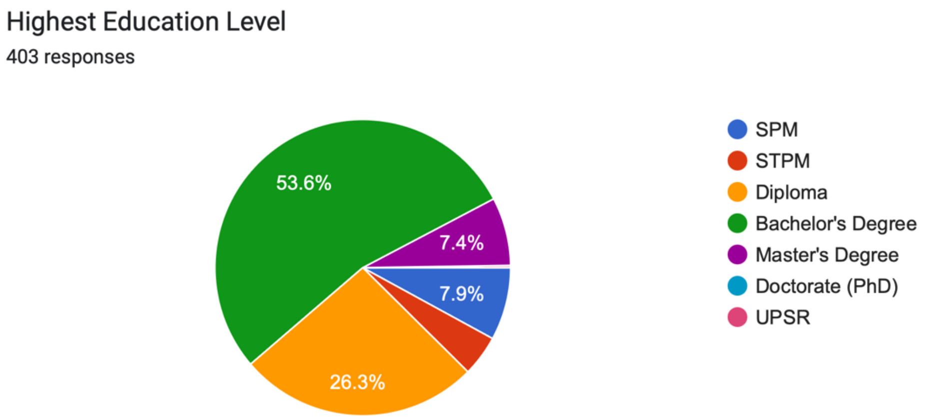
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	206	51.1	51.1	51.1
	Male	197	48.9	48.9	100.0
	Total	403	100.0	100.0	



Highest Education Level

HighestEducationLevel

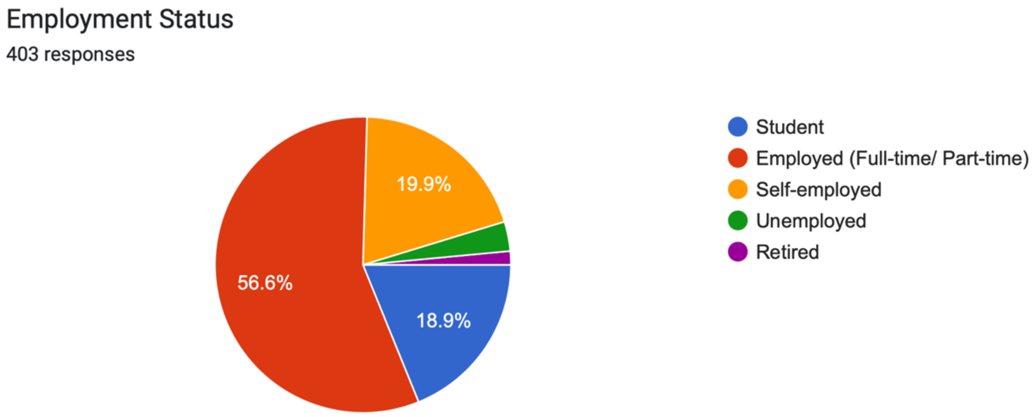
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bachelor's Degree	216	53.6	53.6	53.6
	Diploma	106	26.3	26.30	79.90
	Postgraduate Degree	30	7.4	7.4442	87.345
	SPM	32	7.9	7.9404	95.285
	STPM	18	4.5	4.467	99.75
	UPSR	1	.2	.248	100.0
	Total	403	100.0	100.0	



Employment Status

EmploymentStatus

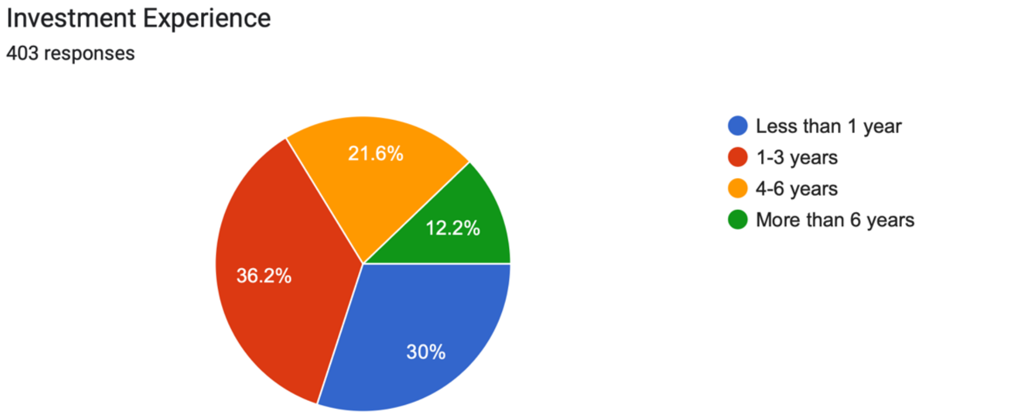
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employed (Full-time/ Part-time)	228	56.6	56.6	56.6
	Retired	6	1.5	1.5	58.1
	Self-employed	80	19.9	19.9	77.9
	Student	76	18.9	18.9	96.8
	Unemployed	13	3.2	3.2	100.0
	Total	403	100.0	100.0	



Investment Experience

InvestmentExperience

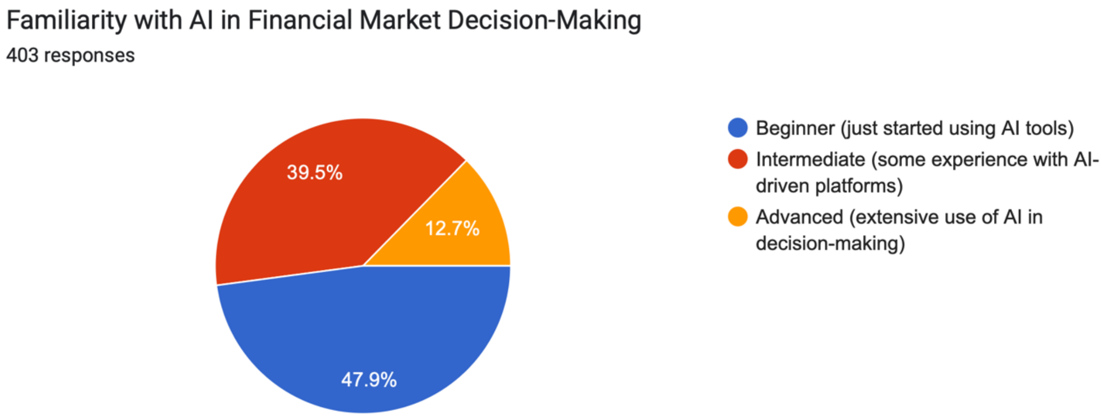
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1-3 years	146	36.2	36.2	36.2
	4-6 years	87	21.6	21.6	57.8
	Less than 1 year	121	30.0	30.0	87.8
	More than 6 years	49	12.2	12.2	100.0
	Total	403	100.0	100.0	



Familiarity with AI in Financial Market Decision-Making

FamiliaritywithAIinFinancialMarketDecisionMaking

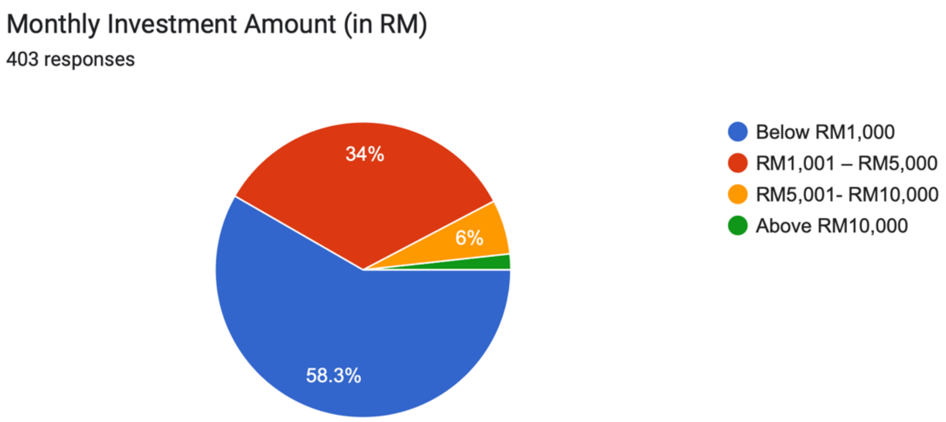
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Advanced (extensive use of AI in decision-making)	51	12.7	12.7	12.7
	Beginner (just started using AI tools)	193	47.9	47.9	60.5
	Intermediate (some experience with AI-driven platforms)	159	39.5	39.5	100.0
	Total	403	100.0	100.0	



Monthly Investment Amount in RM

MonthlyInvestmentAmountinRM

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Above RM10,000	7	1.7	1.7	1.7
	Below RM1,000	235	58.3	58.3	60.0
	RM1,001 - RM5,000	137	34.0	34.0	94.0
	RM5,001- RM10,000	24	6.0	6.0	100.0
	Total	403	100.0	100.0	



Appendix 4.2: Central Tendencies Measurement of Constructs

DV: Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Descriptive Statistics

	Mean	Std. Deviation	N
DV_AI	4.0531	.50120	403
AI1	3.92	.620	403
AI2	4.00	.711	403
AI3	4.13	.648	403
AI4	4.07	.673	403
AI5	4.14	.660	403

IV1: Reduction in Human Bias

Descriptive Statistics

	Mean	Std. Deviation	N
IV_RHB	4.2189	.55614	403
RHB1	4.20	.677	403
RHB2	4.22	.723	403
RHB3	4.03	.819	403
RHB4	4.26	.732	403
RHB5	4.38	.708	403

IV2: Personalized Investment Strategies

Descriptive Statistics

	Mean	Std. Deviation	N
IV_PIS	4.0973	.47449	403
PIS1	4.02	.588	403
PIS2	4.11	.625	403
PSIS3	4.00	.654	403
PIS4	4.07	.703	403
PIS5	4.28	.660	403

IV3: Ethical and Regulatory Challenges

Descriptive Statistics

	N	Mean	Std. Deviation
ERC2	403	4.21	.684
ERC3	403	4.34	.695
ERC4	403	4.36	.732
ERC5	403	4.46	.688
Valid N (listwise)	403		

IV4: Market Adaptation and Technological Barriers

Descriptive Statistics

	Mean	Std. Deviation	N
IV_MATB	4.1514	.51699	403
MATB1	3.80	.786	403
MATB2	4.16	.656	403
MATB3	4.19	.688	403
MATB4	4.25	.730	403
MATB5	4.35	.708	403

IV5: Investor Perception and Trust

Descriptive Statistics

	Mean	Std. Deviation	N
IV_IPT	4.1191	.48202	403
IPT1	4.01	.564	403
IPT2	3.90	.697	403
IPT3	4.07	.609	403
IPT4	4.20	.761	403
IPT5	4.40	.645	403

IV6: Enhanced Market Efficiency and Accuracy

Descriptive Statistics

	Mean	Std. Deviation	N
IV_EMEA	4.1826	.45559	403
EMEA1	4.25	.645	403
EMEA2	4.04	.647	403
EMEA3	4.08	.631	403
EMEA4	4.18	.677	403
EMEA5	4.36	.664	403

Appendix 4.3: Reliability Test

DV: Intention to Adopt AI in Malaysia's Financial Market Decision-Making

Reliability Statistics

Cronbach's Alpha	N of Items
.813	5

IV1: Reduction in Human Bias

Reliability Statistics

Cronbach's Alpha	N of Items
.815	5

IV 2: Personalized Investment Strategies

Reliability Statistics

Cronbach's Alpha	N of Items
.785	5

IV3: Ethical and Regulatory Challenges

Reliability Statistics

Cronbach's Alpha	N of Items
.855	4

IV4: Market Adaptation and Technological Barries

Reliability Statistics

Cronbach's Alpha	N of Items
.772	5

IV5: Investor Perception in Trust

Reliability Statistics

Cronbach's Alpha	N of Items
.783	5

IV6: Enhanced Market Efficiency and Accuracy

Reliability Statistics

Cronbach's Alpha	N of Items
.736	5

Appendix 4.4: Normality Test

Descriptive Statistics

	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
DV_AI	403	-.733	.122	1.656	.243
IV_RHB	403	-.568	.122	.508	.243
IV_PIS	403	-1.030	.122	4.391	.243
IV_MATB	403	-.810	.122	1.587	.243
IV_ERC	403	-.857	.122	1.223	.243
IV_IPT	403	-1.021	.122	3.628	.243
IV_EMEA	403	-.786	.122	2.227	.243
Valid N (listwise)	403				

Appendix 4.5: Pearson's Correlation Coefficient

Correlations

		DV_AI	IV_RHB	IV_PIS	IV_MATB	IV_ERC	IV_IPT	IV_EMEA
DV_AI	Pearson Correlation	1	.561**	.585**	.473**	.435**	.503**	.534**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001
	N	403	403	403	403	403	403	403
IV_RHB	Pearson Correlation	.561**	1	.578**	.498**	.566**	.547**	.586**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001
	N	403	403	403	403	403	403	403
IV_PIS	Pearson Correlation	.585**	.578**	1	.555**	.432**	.579**	.531**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001
	N	403	403	403	403	403	403	403
IV_MATB	Pearson Correlation	.473**	.498**	.555**	1	.485**	.595**	.578**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001
	N	403	403	403	403	403	403	403
IV_ERC	Pearson Correlation	.435**	.566**	.432**	.485**	1	.381**	.480**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001
	N	403	403	403	403	403	403	403
IV_IPT	Pearson Correlation	.503**	.547**	.579**	.595**	.381**	1	.664**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001
	N	403	403	403	403	403	403	403
IV_EMEA	Pearson Correlation	.534**	.586**	.531**	.578**	.480**	.664**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	
	N	403	403	403	403	403	403	403

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

Appendix 4.6: Multiple Regression Analysis

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.673[a]	.453	.445	.37335

a. Predictors: (Constant), IV_EMEA, IV_ERC1, IV_PIS, IV_MATB, IV_RHB, IV_IPT

b. Dependent Variable: DV_AI

Appendix 4.7: Coefficient

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.571	.200		2.858	.004
	IV_RHB	.182	.048	.202	3.764	<.001
	IV_PIS	.307	.054	.291	5.689	<.001
	IV_MATB	.046	.050	.047	.910	.363
	IV_ERC	.077	.051	.072	1.511	.132
	IV_IPT	.067	.058	.064	1.152	.250
	IV_EMEA	.173	.061	.157	2.843	.005

a. Dependent Variable: DV_AI

Appendix 4.8: Multicollinearity Test

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	.571	.200		2.858	.004		
	IV_RHB	.182	.048	.202	3.764	<.001	.480	2.082
	IV_PIS	.307	.054	.291	5.689	<.001	.528	1.894
	IV_ERC1	.077	.051	.072	1.511	.132	.610	1.640
	IV_MATB	.046	.050	.047	.910	.363	.515	1.943
	IV_IPT	.067	.058	.064	1.152	.250	.448	2.234
	IV_EMEA	.173	.061	.157	2.843	.005	.450	2.221

a. Dependent Variable: DV_AI