AI TOOLS MEDIATING THE PERFORMANCE EXPECTANCY OF DIGITAL INVESTMENT PLATFORMS: FROM THE PERSPECTIVE OF GEN Z IN MALAYSIA

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BY

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

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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 23,632 words.

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Thirdly, we would also like to extend our appreciation to our examiner, Puan Wan Rozima Binti Mior Ahmed Shahimi, for spending the time and effort to evaluate our project. This research’s quality and depth have been greatly enhanced by her professional feedback and insightful comments that were offered.

Last but not least, we would like to express our heartfelt appreciation to our team members for their collaboration, dedication, and teamwork during this project. Overcoming obstacles and effectively completing this research has required collective effort, mutual support, and shared determination.

DEDICATION

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PREFACE

This Final Year Project is submitted in partial fulfillment of the requirements for the Bachelor of Finance (Hons) of Universiti Tunku Abdul Rahman (UTAR). The purpose of this research is to examine the factors influencing the performance expectancy of digital investment platforms among Generation Z in Malaysia, with particular emphasis on the mediating role of Artificial Intelligence (AI). The reason as to why we choose this research is to observe the advancement of AI tools and functions in the financial technology sector, especially the digital investment platforms, from the perspective of Generation Z.

This research aims to provide practical insights for investors, innovators and developers, policymakers, and future researchers in understanding the evolving landscape of AI-driven digital investment platforms. Throughout the process of completing this research, we have gained valuable knowledge, research skills, and practical experience. Despite the challenges encountered, this journey has been rewarding and enriching.

ABSTRACT

Financial technology and artificial intelligence (AI) are rapidly transforming. This rapid advancement significantly transformed digital investment platforms, particularly among Generation Z (Gen Z) users. This study examines the factors influencing the performance expectancy of digital investment platforms in Malaysia, with AI as mediator. Grounded in Technology Acceptance Model (TAM) and Artificial Intelligence Device Use Acceptance Model (AIDUA), this study investigates the effects of social influence, perceived usefulness, perceived ease of use, and hedonic motivation on performance expectancy. This study employed a quantitative research design through a structured questionnaire. The data were collected from 446 respondents, primarily Gen Z. After that, the data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) on SmartPLS. All independent variables, social influence, perceived usefulness, perceived ease of use, and hedonic motivation have significant positive effects on performance expectancy. Furthermore, this study found that AI significantly mediates the relationships between perceived usefulness, perceived ease of use, hedonic motivation, and performance expectancy. However, its mediating role is insignificant between social influence and performance expectancy. The model in this study shows moderate explanatory power, indicating that AI plays a critical role in enhancing users' expectations of digital investment platforms. This study contributes to the understanding of AI-driven financial behaviour among Gen Z and insights for fintech developers and policymakers to enhance user engagement and platform performance.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AIDUA	Artificial Intelligence Device Use Acceptance Model
AVE	Average Variance Extracted
DAX	Digital Asset Exchange
DIM	Digital Investment Manager
ETP	Electronic Trading Platform
FinTech	Financial Technology
f^2	Effect Size
Gen Z	Generation Z
HM	Hedonic Motivation
HTMT	Heterotrait-Monotrait Ratio
ICT	Information and Communication Technology
P2P	Peer-to-Peer
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PLS-SEM	Partial Least Squares Structural Equation Modeling
PU	Perceived Usefulness
Q^2	Predictive Relevance
R^2	Coefficient of Determination
R&D	Research and Development

SEM	Structural Equation Modeling
SI	Social Influence
TAM	Technology Acceptance Model
4^{th} IR	4^{th} Industrial Revolution

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CHAPTER 1: INTRODUCTION

1.0 Introduction

Digital investment platforms are segments that are rapidly gaining the attention of digital users in the Fintech industry due to its ability in enabling individuals to access and manage investments through digital platforms anytime, anywhere. This rapid development has transformed the investment behaviour, particularly among younger investors such as Gen Z, and raised important concerns regarding trust, usability, and adoption. This chapter starts with the context of this study, followed by the issues arouse. The objectives and questions of this study are then determined. Moving on, the significance of study is further discussed, highlighting the benefits of this research to different stakeholders.

1.1 Research Background

The technological revolution that society has undergone particularly in the 21st century, is known as the Fourth Industrial Revolution (4th IR) (Ross & Maynard, 2021). According to Pellicelli (2023), it is the transformation process of the industry through intelligent networking of machines and processes with the assistance and combinations of information and communication technology (ICT). Artificial intelligence (AI), machine learning, and robotics are combined with huge computing power and big data which drives technological developments that enhances productivity, automation and outcome (Jindala & Sindhu, 2022). The ability of machines to be trained to learn and solve problems by themselves instead of instructing them to do something has indeed changed the way the world is working now (Sahai & Rath, 2021). Şimşek Demirbağ and Yıldırım (2023) studies the impact of the 4^{th} IR and found that employment, productivity, quality 4.0 (customer satisfaction), flexibility, and innovation are the top advantages of 4^{th} IR, whereas financial difficulties, technical difficulties, and cybersecurity are the top disadvantages of Fourth Industrial Revolution. While the Fourth Industrial Revolution brought various opportunities and advantages, developing countries continue to lag behind due to different challenges faced. Oyebanjo and Tengeh (2021) stated that the Fourth Industrial Revolution is a daunting prospect for less-developed nations such as Africa without sufficient human resources who are exposed to technological advancement.

Over the past ten years, the development of financial technologies contributed to the creation of various business and organisational models encompassing various innovations in methods and techniques, this is known as digital transformation in the financial industry (Benković et al., 2023). By this, digital transformation enhances the productivity and efficiency in the financial industry by automated processes, real-time decision making, and financial inclusion through technologies such as AI (Syah & Anca, 2025). In the financial services sector, Fintech firms, technological firms and regulators are actively collaborating to develop digital financial services such as smart system of banking, investing and insurance services (Yun et al., 2021). According to Mpofu (2024), the use of digital financial services brings benefits such as broadening financial inclusion, promoting innovation in the financial sector, and possible increased economic growth. The adoption of digital financial products and services such as digital accounting and Fintech innovation drives business performance (Al-Okaily et al., 2024; Rahman & Abedin, 2021). In this situation, all-encompassing support tools are required for the development of digital financial innovations, the promotion of digital start-ups, and the deployment of digital financial technology (Vardomatskya et al., 2021). Global acceptance of new technologies is an inevitable response to the successful development of flexible and efficient digital technologies (Hamad & Jawad, 2024).

According to Shahbaz et al. (2022), the E7 economies which include Brazil, Indonesia, Mexico, India, Turkey, Russia and China shows a positive effect between the advancement in technology and institution quality, bank finance, foreign direct investments, and income. Gu et al. (2021) found similar results which states that technological innovation, income, and research and development (R&D) are significantcharacteris factors in affecting the financial development of E7 economies in the long run. He et al. (2021) studied the trend of technological innovation in China from 1990 to 2017 and found that R&D, non-bank financing, and real GDP promote technological innovation. From the perspective of Oman, the banking industry has been constantly implementing new methods which strengthens the financial intermediary process that increases financial inclusion to all sectors and fosters business opportunities (Stephen et al., 2022). It is observed that different countries experience different effects brought by the Fourth Industrial Revolution. While Malaysia has made notable progress in digital connectivity and infrastructure, various factors such as development of human resources, and digital literacy are crucial for long-term sustainability (Chong et al., 2025).

The ability for people or enterprises to obtain financial services and products that suit their needs is known as financial inclusion (World Bank Group, 2025). Financial inclusion can be facilitated through the adoption of digital services which reaches out to those in underserved areas, bridging the digital division while in the meantime promoting sustainable development (Lung, 2024). As observed in Table 1.1, Malaysia's Financial Literacy Score stands at 59.7, slightly lower as compared to the mean of 26 other countries with a score of 60.5, and OECD countries with a score of 62.0 (Bank Negara Malaysia, n.d.a). Despite the lower-than-average financial inclusion score, Malaysia has achieved notable outcomes with a surge in the data of sub-districts having access to financial services from 46% in 2011 to 96% in 2020. The financial literacy scores positively influence the adoption of Fintech in a study in Bangladesh (Islam & Khan, 2024). Therefore, it is worth identifying the extent of influence of financial literacy score in Malaysia towards the investment decision of Gen Z in Malaysia.

Table 1.1: *Financial Literacy Score of Malaysia as Compared to OECD Countries*

	Malaysia	**Average**	**OECD**
Financial Behaviour	68.1	59.2	59.2
Financial Knowledge	52.3	62.8	65.8
Financial Attitude	54.9	59.2	61.6
Financial Literacy Score	**59.7**	**60.5**	**62.0**

Source: Bank Negara Malaysia (n.d.a).

Fintech applications include online peer-to-peer (P2P) lending, crowdfunding, digital wallets and more which enable secure, efficient transactions and investment management (Yanida et al., 2025). While P2P lending platforms, crowdfunding, and digital wallets are widely researched, digital investment platforms, which is one of the Fintech services is rarely investigated. A digital investment platform allows investment activities to be made online for various options such as stock investment, mutual funds, gold investments, and government bonds (Vici & Nuryasman, 2022). Digital investment platforms offer various benefits such as more transparent information, rapidity in investing, and lower operational costs which allow investors to make quick and decisive decisions appropriately (Zamzami, 2021). Countries such as the United States, Hong Kong SAR, China, Singapore, and the United Kingdom are large in financial centers with high equity investments (World Bank Group, 2022). According to the Ministry of Digital (2024), the digital investment value soared to RM66.22 billion in the first half of year 2024 as compared to the digital investment value of RM46.2 billion in FY2023. This signals a robust growth and resilience of digital economy in Malaysia.

Some examples of digital investment platforms in Malaysia include Digital Investment Manager (DIM), Digital Asset Exchange (DAX), and Electronic Trading Platforms (ETP). According to Securities Commission Malaysia (n.d.a), some licensed Digital Investment Manager (DIM) include Akru Now Sdn Bhd, Kenanga Investment Bank Bhd, and StashAway Malaysia Sdn Bhd, whereas Luno Malaysia Sdn Bhd, HATA Digital Sdn Bhd, and MX Global Sdn Bhd are some licensed Digital Asset Exchange (DAX). BTBS, FXall, and Instimatch Global are some licensed Electronic Trading Platforms (Bank Negara Malaysia, n.d.b). Moomoo Securities Malaysia Sdn Bhd and Rakuten Trade are also some other well-known licensed and regulated brokers in Malaysia under the Capital Markets Services License by the Securities Commission Malaysia.

The Digital Investment Management (DIM) framework was introduced in 2017 by the Securities Commissions Malaysia which enables market participants to embrace digitisation and that provides more innovative capital market products and services to investors (Securities Commission Malaysia, 2017). As of 2023, the total DIM AUM has grown 400 times since 2018 with a steady upward trend of 15% growth in year 2023, with 51% of users are in their 20s. Moreover, retail investors made up over 72% of the investor segment across regulated DAXs, resulting the primary asset class below the age of 45 (Securities Commission Malaysia, n.d.b).

Financial organisations are leveraging digital platforms and Artificial Intelligence (AI) to provide enhanced services to users. AI-powered algorithms exceed the ability of human in processing vast amounts of information in a short period of time, resulting in improved price discovery and reduced transaction costs (Alekseenko, 2023). This developed robo-advisors, which are algorithm-based digital products that utilises complex datasets and algorithms to offer customised solutions. Robo-advisors are one of the prominent applications in the financial market as it improves the efficiency in investing and maintaining investment portfolios (Khanna & Jha, 2024). The ability of robo-advisors in leveraging sophisticated algorithms and machine learning enhances platforms by offering personalised financial advice and automated portfolio management without the need for human intervention. Tailored investment plans can be created based on the analysis of robo-advisors through market trends, client preferences, economic indicators, and risks (Varghese et al., 2024).

Malaysia has also integrated AI technology into the financial sector such as investing activities to create robo-advisors that offer automated investment management services (Zheng et al., 2021a). According to Hatta et al. (2022), the proposed Savings2u, a financial robo-advisor focus on savings and Shari'ah compliance investment features according to customer's risk preference to create and manage the portfolio automatically. However, Barile et al. (2024) mentioned that relying solely on algorithms is not feasible whereas a hybrid approach with human interaction enhances the decision-making process. It is found similar from According to Ahmad and Mokal (2024) investment professionals can access cutting-edge capabilities in the process of analysing data, predicting analytics, and managing portfolio by utilising AI tools.

Despite the growth of digital investment platforms in Malaysia, there is still limited studies and research in understanding the way investors, especially Gen Z who are digitally literate generations, perceive and adopt these platforms. Exploring this area is essential to align to Malaysia's digital finance agenda with the opportunities of the 4th IR.

1.2 Research Problem

The integration of artificial intelligence (AI) tools in financial decision-making helps improve predictive accuracy with less response times especially in volatile markets (Arifian et al., 2024). The integration of AI into portfolio management allows for the rapid processing of extensive financial datasets, the extraction of critical insights, and the assessment of potential risk factors, thereby improving decision-making accuracy, strengthening risk analysis, and enhancing portfolio performance, which collectively drive greater investor adoption of AI-based tools (Alfzari et al., 2025; Bi et al., 2024). It not only effectively assists investors to achieve their financial goals but also efficiently provides information and advice. However, it may also introduce risks such as data privacy and algorithmic accountability (Akter et al., 2021; Gupta et al., 2025; Sharmila & Singh, 2024).

One of the main challenges of using AI in financial investment decisions among Gen Z investors is the issue of data privacy. AI technologies influence psychological privacy decision-making frameworks such as social influence, affecting users' adoption in financial context (Afroogh et al., 2024; Martin & Zimmermann, 2024). Liang and Lu (2025) also found that robo-advisory platforms demand large amount of data and have ambiguous privacy policies, so concerns about privacy and regulatory complexity may reduce the perceived ease of use of digital investment platforms. Although AI can effectively enhance financial decision-making, concerns over data privacy still pose a significant risk to users (Huang, 2023; Williamson & Prybutok, 2024). In financial aspects, adoption of AI in business process raises critical concerns about data security, bias, and regulatory compliance (Buczynski et al., 2025; Gupta et al., 2025). Research conducted by Saura et al. (2022) showed that citizens worry about how government use their data to analyse their behaviour by AI. Similarly, in the context of digital investment platforms, Gen Z investors may also worry about how AI-driven systems use their financial and personal data (Liang & Lu, 2025). This proves that Gen Z investors are concerned on the ethical data governance raised by AI in terms of digital investment platforms, which is part of the reason which halts them from adopting new digital investment platforms.

Moving on, another significant risk of using AI in financial investment platforms is the issue of algorithmic accountability. Algorithmic bias has been widely discussed in data-driven innovation, leading to fear of AI adoption (Akter et al., 2021; Kordzadeh & Ghasemaghaei, 2021). This has proven that discriminatory or unfair decisions may slow down AI adoption. According to Grimmelikhuijsen (2022) and Tamraparani (2022), explainability matters more than just giving access to algorithm details, so transparency is a critical factor in fostering safe adoption of AI. When AI decisions are easy to understand with clear transparency, people can safely use AI. However, Khosravi (2024) stated that the increasing technical complexity of machine learning algorithms poses challenges for perceived ease of use and explainability. As AI models get more complex, they will become harder for users to understand. If investors could not understand how AI makes decisions, they may perceive the platform as complex and unhelpful or even not expect it to perform reliably. On the other hand, by addressing emotional biases and incorporating emotionally intelligent design, robo-advisors can empower investors to make better financial decisions and achieve long-term goals (Sharmila & Singh, 2024). This illustrates how important hedonic motivation and perceived usefulness are in influencing adoption. Sharmila and Singh (2024) also stated that the challenge of integrating emotional intelligence into robo-advisors also intersects with issues of algorithmic bias, transparency, and user trust. This created the trade-off between emotional intelligence and algorithmic accuracy. This further emphasizes the need for responsible adoption of AI in financial platforms. Therefore, fairness and explainability are crucial to drive AI adoption of Gen Z investors in digital investment platforms.

According to past research by Pramod et al. (2024), the research investigated elderly citizens' acceptance generative artificial intelligence. Similarly, Tan et al. (2023) conducted a research to examine millennials' adoption of robo-advisor in terms of financial knowledge. However, Tan et al. (2023) and Pramod et al. (2024) limited the applicability of findings to developing or emerging markets among Gen Z demographics as they are more digital literate compared to older generations. Hoffmann and Nurski (2021) and McElheran et al. (2024) also conducted research to investigate AI adoption in America and Europe. Nevertheless, the findings from Hoffmann and Nurski (2021) and McElheran et al. (2024) may not fully apply to emerging markets like Malaysia, where Gen Z investors are only beginning to adopt such technologies. Chan and Lee (2023) found Gen Z's higher level of digital literacy compared to elder generations as they expressed optimism and strong intentions to use generative AI in their learning. In the context of financial investment, Gen Z may also apply generative AI such as robo-advisors on their decision-making. The finding of Chan and Lee (2023), Hoffmann and Nurski (2021), and McElheran et al. (2024) also did not examine the AI adoption among younger generation in developing countries, leaving a gap in understanding how Gen Z investors in Malaysia, an emerging market, form their performance expectancy of digital investment platforms. In this context, the presence of AI mediates the relationship between social influence, perceived ease of use, perceived usefulness, and hedonic motivation with performance expectancy, as AI features enhance platform functionality, usability, and enjoyment while shaping Gen Z investors' adoption. Hence, there is a lack of research on how Gen Z investors in emerging markets like Malaysia perceive AI adoption in financial investment platforms. This presents a significant research gap, as the rapid developing Fintech situation in Malaysia requires a deeper comprehension of how AI influences Gen Z investors' decision-making in financial aspects and the use of digital investment platforms.

1.3 Research Objectives

1.3.1 General Research Objectives

The general objective of this research is to examine the factors that influence the performance expectancy of digital investing platform.

1.3.2 Specific Research Objectives

The objectives listed below serve to address the key variables and relationships examined in this research:

i. To study the significant relationship between social influence, perceived usefulness, perceived ease of use, and hedonic motivation to the performance expectancy of digital investing platform in Malaysia.

ii. To study the significant relationship between AI mediating role to the performance expectancy of digital investing platform in Malaysia.

1.4 Research Questions

Two research questions must be formulated to guide the course of this investigation:

i. Is there a significant relationship between social influence, perceived usefulness, perceived ease of use, and hedonic motivation on the performance expectancy of digital investing platform in Malaysia?

ii. Is there a significant relationship between AI mediating role to the performance expectancy of digital investing platform in Malaysia?

1.5 The Significance of Study

1.5.1 Gen Z Investors

The present study is important as it provides a valuable insight into the adoption of new technologies such as digital investment platforms with the mediating effect of Artificial Intelligence (AI) among Gen Z investors in Malaysia. The focused demographic of Gen Z highlights digital natives who are highly literate in technology but are new to financial investing and perceive to the integration of AI in their financial decision making. This is relatively important in research as Gen Z represents the next major investor group whose behaviour shapes the future investment landscape of Malaysia, and even globally.

For investors, this study contributes in several important ways. Firstly, it helps Gen Z investors understand the possible benefits and risks of using AI-driven investment platforms better. While these platforms provide predictive accuracy, portfolio optimisation, and real-time insights, challenges such as data privacy, algorithmic accountability, and transparency are crucial to be understood and be aware of. By raising awareness of these possible issues, Gen Z investors can make more informed financial decisions when engaging with robo-advisors and digital financial tools. Next, this research benefits Gen Z investors by identifying the factors which most influence their intention in adopting a new technology. For instance, social influence, perceived usefulness, perceived ease of use, and hedonic motivation may enable investors to assess new platforms and technologies more skilfully.

Ultimately, this study benefits Gen Z investors by allowing them in understanding their own behaviour in adopting a new technology and making financial investment decisions, with the hope of balancing technological innovation with ethical considerations.

1.5.2 Developers and Innovators

This study provides crucial insights for developers and innovators in the Fintech industry in understanding how Gen Z investors perceive and adopt digital investment platforms with Artificial Intelligence (AI). As Malaysia's financial sector is steadily undergoing rapid digital transformation, understanding the expectations, preferences, and concerns of the next dominant users of digital platforms will help developers and innovators develop and design more user-centric and trustworthy digital platforms.

This study identifies several key factors in influencing the performance expectancy of digital investment platforms which eventually affects the adoption of Gen Z investors in digital investment platforms. The factors include social influence, perceived usefulness, perceived ease of use, and hedonic motivation. The mediating role of AI in affecting the performance expectancy of digital investment platform is also worth examining. For developers and innovators, these findings provide a more practical framework which aligns product design to user preferences. Besides, understanding the possible risks and concerns of Gen Z investors towards digital investment platforms allows developers and innovators to strengthen their platforms that overcome potential issues. For instance, insights of fear towards data privacy allow developers and innovators to design more transparent algorithms and establish clear communication regarding data usage. Also, understanding the factors influencing the financial decisions of Gen Z investors helps developers and innovators to strike the right balance between advanced functions and analytics while striving to be a user-friendly platform. Developers or innovators can tailor solutions to the specific needs and preference of Gen Z investors such as real-time market insights with emotionally intelligent robo-advisory features which creates satisfaction among users when using the digital investment platform.

Through this research which provides evidence-based knowledge of Gen Z investors user behaviour, expectations, and concerns, developers and innovators can innovate digital investment platforms that are not only technologically advanced but also user-friendly, trusted, ethical, and adaptable to the financial needs of the next generation of investors, who will be Gen Z.

1.5.3 Government

The emergence of digital investment platforms has significant change traditional investment processes. With the rapid growth, individuals are more encouraged and easily to participate in investing. This development not only brings benefits to Gen Z investors, who are the focus of this research, but also important for the government, who plays a central role in creating a secure system for the digital financial sector.

This study provides valuable insights for the government from the perspective of Gen Z investors who are digital natives and represent the future of the financial sectors. Through the measurement of the performance expectancy of digital investment platforms, government as policymakers can design policies and regulatory frameworks that strengthen the digital security and protect the public investors. This includes ensuring digital security, establishing robust mechanisms and addressing risk issues. Given the importance of investors protection and responsible innovation, government must strike a balance between the financial technology growth and mitigating the risks, such as fraud, data breaches, and misuse of technology. Furthermore, this research can enhance the digital financial literacy especially in the areas that involve advanced technologies like Artificial Intelligence (AI). A study by Lee et al. (2022) mentioned that during COVID-19 pandemic, improved individual financial literacy and substantial government fiscal stimulus has encouraged investors to invest in various financial assets. In this context, the study assists the government in promoting a secure, equitable, and innovative investment landscape, which is aligned with the nation's digital economy goals.

In addition, this research helps highlight the regulatory challenges of AI adoption in the financial sector. As AI-driven tools are increasingly incorporated into investment platforms and technologies, ethical data governance must be addressed. In this case, the government could use the findings of this study to anticipate potential risks arising from the Gen Z investors' perspective to proactively establish standards for responsible technological use in financial services. This strengthens and enhances the competitiveness of financial services and platforms, contributing to a more resilient and sustainable financial system in Malaysia.

1.5.4 Future Researchers

This study is significant for future researchers, particularly within the Malaysian context. This is due to the limited academic investigations and studies regarding the adoption of AI-driven digital investment platforms in Malaysia. While studies on AI adoption and technology adoption have been studied, most of the existing literature focuses on developed markets such as the United States, Europe, or China. By addressing the study gap of Gen Z investors in emerging markets such as Malaysia, this research contributes new insights to the field of financial technology adoption.

For future researchers, the findings in this study provide a valuable foundation for comparative analysis. Notably, the theoretical framework of this study incorporates two different theories which are Technological Acceptance Model (TAM) and AI Device Usage Acceptance model (AIDUA). Therefore, the independent variables are a combination of both underlying theories to form a new area of study. A framework of social influence, perceived usefulness, perceived ease of use, and hedonic motivation, with AI as a mediating factor offers a model that can be further tested, refined or extended to other digital financial services in the future. Future researchers may then explore these dimensions in greater depth such as investigating the psychological impact of investment tools that are powered by AI not only in the short-term but also long-term on Gen Z investors.

In essence, the rarity of this study within the Malaysian context focused on the demographic of Gen Z investors enhances its academic contribution and the insights generated can guide future researchers in designing more comprehensive research and studies. Not only can this research establish as a knowledge base in the financial sector, but it can also pave the way for further advancements in other sectors and field.

1.6 Conclusion

This chapter begins with the overview of the Fourth Industrial Revolution and development of digital investment platforms as the background of this research to provide a clear context for the research study. The research problem which highlights the key issues that form the basis of this research is then being outlined. The research objectives and research questions are then subsequently introduced to guide the direction of this research. Following this, the significance of research is discussed to demonstrate the relevance and potential contribution of this research to possible parties.

CHAPTER 2: LITERATURE REVIEW

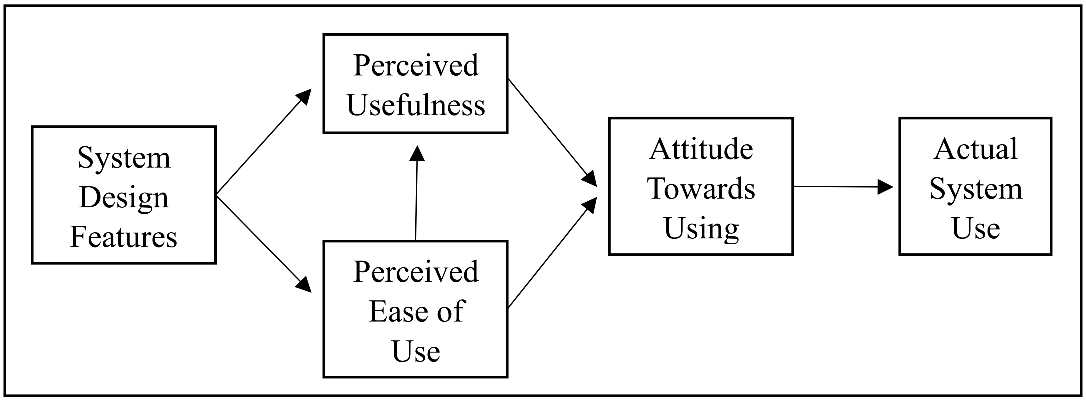
2.0 Introduction

This research reviews some theoretical and empirical literature underpinning the span of study of research, specifically focusing on the factors that influence performance expectancy of digital investment platforms among Gen Z. The four independent variables studied under this research are Social Influence (SI), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Hedonic Motivation (HM). These are examined in relation to the dependent variable which is Performance Expectancy of Digital Investment Platform (PE) with AI tools (AI) serving as a mediating factor. This research draws upon established underlying theories which include Technology Acceptance Model (TAM) and Unified Theory of Acceptance and AI Device Use Acceptance Model (AIDUA) alongside with relevant empirical studies. By synthesising existing literature reviews, this chapter aims to identify gaps in past research, establish theoretical foundation and proposed conceptual framework, and justify hypothesised relationships between variables. Ultimately, this chapter explores the role of AI acting as a bridge between the independent variables and dependent variable, influencing the decision of Gen Z investors in choosing digital investment platforms.

2.1 Theoretical Framework

2.1.1 Technology Acceptance Model (TAM)

Figure 2.1: Technology Acceptance Model



Source: Davis, F. D. (1989)

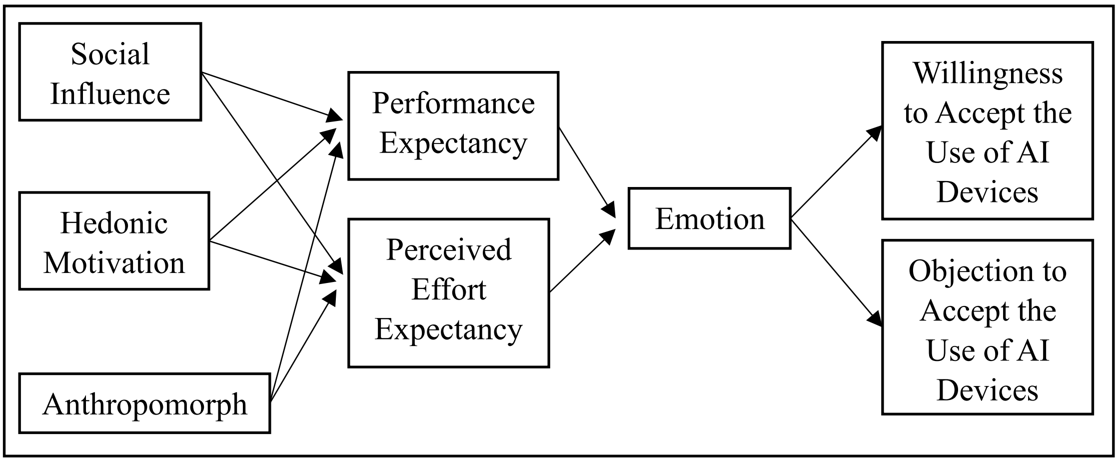
The Technology Acceptance Model (TAM) introduced by Davis (1989) posits that the key factors driving users' intention to adopt a technology are primarily perceived usefulness and perceived ease of use.

The degree to which a person thinks utilising a particular system will help them accomplish their objectives or perform better at work is known as perceived usefulness (Davis, 1989). A useful digital investment platform may convince investors to use it by providing superior performance. In the context of digital investment platforms, perceived usefulness may refer to how much investors think the platforms may enhance profits in comparison to traditional techniques, improve investment decision-making, and offer thorough market data (Lee, 2009). Usefulness of digital investment platforms thus increase investors' intentions to use such platforms. Previous research studies have shown that perceived usefulness has s positive relationship with behavioural intention to use technology as users have a higher tendency to adopt a new technology once they have trust in which it can enhance their productivity or outcomes (Venkatesh & Davis, 2000; King & He, 2006; Chen et al., 2025; Alshammari & Babu, 2025). If digital investment platforms' performance is superior to traditional, it may be perceived as useful. With useful AI tools, investors may adopt digital investment platforms to achieve their financial goals (Seiler & Fanenbruck, 2021; Sembiring, 2022; Chanddru, 2025).

On the other hand, perceived ease of use is the degree to which an individual believes that using a certain system will not require effort (Davis, 1989). Technology nowadays is advanced, so it requires less effort to be adopted. Perceived ease of use is not only a factor of behavioural intention but also an antecedent of perceived usefulness since technologies easier to use are often seen as more useful (Gefen & Straub, 2000). It also explains the actual adoption of fintech such as mobile wallets (Chong et al., 2024). In technology adoption, perceived ease of use may include how easily the technology is learned, used, and operated (A'la et al., 2020). Prior research demonstrated that a system increases users' satisfaction and continuous usage when it is viewed as simple (Nazim et al., 2024; Istiqomah & Alfansi, 2024; Yao & Wang, 2024). Perceived ease of use can lead users to have intents to use an AI application (Chen et al., 2025; Abdullah et al., 2025). Furthermore, it positively impacts the use of financial technology both directly and indirectly (Wibisono & Ang, 2019; Widiastuti & Hayati, 2019; Pridayanti & Wiagustini, 2021). If digital investment platforms are easy to use than traditional, investors are more likely to adopt them.

2.1.2 Artificial Intelligence Device Use Acceptance (AIDUA)

Figure 2.2: Artificial Intelligence Device Use Acceptance



Source: Gursoy et al. (2019)

Gursoy et al. (2019) introduced the Artificial Intelligence Device Use Acceptance (AIDUA) model, which offers a multi-stage framework for comprehending how consumers choose to embrace AI-driven devices, with hedonic motivation and social influence playing key roles.

Social influence refers to the extent to which individuals perceive that other important peers, influencers, or family believe they should adopt a technology (Gursoy et al., 2019). When important others think that an individual should adopt certain technology, the individual is likely to use it. In context of technology adoption, desire to maintain a positive social image may drive individuals' intentions to adopt AI, aligning with group norm (Gursoy et al., 2019). One of the things influencing consumers' intentions to utilise particular technologies could be this social pressure. Various past studies have shown that social influence is significant in performance expectancy, influencing behavioural intention to adopt technology (Cao & Chun, 2024; Alhindi & Sivakumar, 2025; Bai & Yang, 2025; Lai et al., 2025). To illustrate, in Indian hospitality sector, social influence significantly and positively impacts performance expectancy, indicating that endorsement from others can enhance perceptions of AI's usefulness (Roy et al., 2020). In the context of AI-enabled investment platforms targeting Gen Z investors, social influence should be crucial due to generation's high engagement with social networks and online communities.

Hedonic motivation in AIDUA model refers to the degree of enjoyment or intrinsic satisfaction when individuals are using the technology (Gursoy et al., 2019). When users feel satisfied while using the technology, they are more likely to continue using certain technology. Research has shown that hedonic motivation can be a strong determinant of behavioural intention (Chi et al., 2020; Bai & Yang, 2025; Lai et al., 2025). Hedonic motivation not only fulfilled users' satisfaction in AI but also in the context of financial technology. For instance, hedonic motivation was found to positively influence technology-related behaviour in various digital context, such as AI devices in banking and e-wallets (Mei, 2024). In AI-powered investment platforms, features such as real-time personalised insight, gamified achievement badges, and interactive learning modules can enhance enjoyment and thus strengthen behavioural intention. As financial services continue to digitize, hedonic motivation might be increasingly crucial for attracting Gen Z investors.

Social influence has a beneficial impact on the intention to use social media, according to a TAM-based study of social media adoption by Bashir et al. (2022). Kumaran et al. (2024) discovered that hedonic motivation moderates the link between perceived usefulness, perceived ease of use, and customer purchasing behaviour in another study of social commerce adoption based on TAM. Cho & Son (2019) extended TAM to include social influence and hedonic motivation in their study about social commerce, so TAM's ability to explain technology adoption can be strengthened. In present research, social influence and hedonic motivation are integrated into the conceptual framework to capture both social pressure and intrinsic enjoyment factor that may influence Gen Z's performance expectancy of digital investment platform.

2.2 Empirical Review

2.2.1 Performance Expectancy of Digital Investment Platform (PE)

In recent years, the integration of AI tools and advanced technologies have rapidly utilised and benefited to younger generation, Gen Z. Most of them use digital investment platforms or any fintech financial tools such as robo-advisory and automated portfolio management for financial investment decision. Research shows that there are more than 50% individuals aged between 18-24 adopt generative AI tools in both personal and professional contexts (Visnu, 2024). Azhar et al. (2023) define performance expectancy as the degree to which a person believes that utilising cutting-edge technology will improve their work performance.

Based on Urus et al. (2024), it shows that performance expectancy is significantly influenced on the adoption of fintech payment services among young generation. The individuals are more willing to adopt financial tools which would enhance their efficiency and financial decision-making. Duong (2024) mentioned that performance expectancy is positively associated with the actual use of investment platforms. Abdullah et al. (2024) also highlights that performance expectancy has significant relationship towards the intention in Fintech adoption. In the article of Al-Okaily et al. (2022), it has a same conclusion with Azhar et al. (2023) about performance expectancy. They mentioned about a fintech user is more willing to apply the technology tools after they experienced its benefits such as time efficiency, competitive cost, and environmentally friendly (Sri et al., 2022). Thus, the developers should consider enhancing their financial services to provide users a better performance.

Furthermore, performance expectancy is consistent in affecting the adoption of Fintech such as Internet banking and mobile banking (Chan et al., 2022). Wati et al. (2024) also shows that performance expectancy has a positive relationship with the intention of using mobile banking in Surabaya. Moreover, Faizal et al. (2023) found that performance expectancy is significant bring positive effects on the user's behaviour intention to use mobile banking. The Indonesia banking users are willing to adopt the new "Livin by Mandiri" app if it offers good performance in mobile banking. Nevertheless, the research of Shaikh et al. (2021) shows that performance expectancy has insignificant relationship with the adoption of mobile banking. As most of the people who have no or little experience with digital services, might not understand the importance of performance expectancy. Hence, mobile banking is not included in this research, as it focusses more on the bank sector but not the digital investment platforms or fintech.

Additionally, psychological factors also play a significant role to influence performance expectancy. According to Ratnawati (2024), it highlights that people involved in investing are not only consider expected performance of their investment's tools but also assess into psychological factors that significantly impact on their decision-making. Psychological factors such as overconfidence bias, fear of missing out, and herding bias are impact to the investment decision-making (Maheshwari & Samantaray, 2025). Besides, Adiputra et al. (2021) also mentioned that psychological factors like overconfidence, herding effect, and self-monitoring will have positive relationship with investment decision-making that will bring impact on investment performance. However, Bland et al. (2024) said that perceived risk is negatively impacting to the performance expectancy of investments. Perceived risk is one of the psychological factors that refer to degree of uncertainty that an individual encounters when making decisions, which reflects the possibility for unfavourable outcomes such as dissatisfaction, or lower quality than expected (Van et al., 2021). Therefore, in this research, psychological factors are excluded, as they relate primarily to human behaviours.

2.2.2 Social Influence (SI)

Social influence refers to the degree to which an individual is influenced by others in believing he or she should adopt the technology during the process of technology acceptance (Gopinath & Narayamurthy, 2022). Social influence is seen as an important factor in influencing individual decisions as people tend to change their opinions to follow the opinion of the majority in a group (Zheng et al., 2021b). Social influence is seen to positively affect the intention of adoption of Fintech services (Irimia-Diéguez et al., 2023; Xie et al., 2021). Individuals tend to observe the people surrounding's behaviour as a guide to their own actions. When families, friends, or influential figures starts to adopt and benefit from Fintech services, it creates a sense of social proof (Gharaibeh, 2024). Given that digital investment platforms are considered as a Fintech service which offer AI-driven tools such as automated portfolio management, robo-advisory and real-life market analysis, it is worth in determining whether the effect of social influence apply in this context, especially for the demographic of Gen Z.

In terms of studying the impact of social influence towards the adoption of digital investment platforms among Gen Z, it is important to refer to relevant digital platforms or applications prior to the widespread of AI tools in the field of finance. Prastiawan et al. (2021) studied that social influence has a positive impact towards the use of mobile banking in Indonesia. Besides, Trivedi et al. (2022) discovered that consumers' intention to pay for mobile apps is most influenced by social influence. From the perspective of Gen Z, the adoption of mobile payment in Taiwan is significantly impacted by social influence positively which improves the behavioural intentions of young generations as a result (Wei et al., 2021). Gan et al (2021) shows that the adoption of financial robo-advisor during COVID-19 crisis in Malaysia relies positively on the social influence according to UTAUT model. Thus, the relationship between social influence and adoption of digital investment platforms is worth researching as it provides a deeper insight into whether the same social influence mechanism is observed in AI tools in digital investment platforms, which is a part of the Fintech services context.

Social media can also be regarded as a form of social influence which shapes individual's perceptions and adoption decisions from the influence of users of social media. Joseph et al. (2025) shows a significant positive relationship between the adoption of Fintech and social media use as a platform for dissemination of information regarding investment decisions. Social media information impacts the investing decision of investors. Investors who use social media for investment information have a higher tendency in investing in cryptocurrencies or using mobile trading applications (Kim & Fan, 2025). This opens the opportunity for financial professionals to engage in social media as a mean to inform more young adults about investment opportunities due to the positive relationship between social influence and the decision of adoption of technology (Vishnu et al., 2023).

Moreover, social influence has a positive and considerable direct impact on millennials' behavioural intention in using securities crowdfunding platform due to the trust new users develop towards the platform (Febrianti & Darma, 2023). As mentioned by Soeta et al. (2023), social influence is highly required to increase investors' trust in using and investing in a P2P lending platform. Trust is important as it involves the level of risk in trying out in adopting a new financial service. While past research has been centred on other Fintech services such as P2P lending platform, the present research indulges into a new Fintech service, digital investment platform, to determine whether the adoption of digital investment platforms react similarly to the then P2P lending platform based on factors such as social influence. The usage of Fintech services such as digital payment systems relies heavily on the social influence in the acquisition of information (Oktafian, 2022). These findings indicate that the adoption of Fintech services often relies heavily on social influence in seek of validation and shared experiences from people surrounding them before adopting a new technology. The factors influencing the adoption decision varies from different levels of investment experiences. While novice investors are more likely to adopt digital investment services, experienced investors tend to rely more on self-reliance (Soebdhan, 2023). Consequently, understanding how social influence drives Gen Z's willingness in adopting AI investing tools in digital investment platforms is essential.

Nevertheless, Singh et al. (2020) found social influence has a significant negative influence towards the behaviour intention of using Fintech services. A research by Urus et al. (2022b) also stated that the adoption of Fintech payments is not influenced by the surrounding environment but the voluntary action of the particular individual to adopt. Similar results are obtained by Handarkho et al. (2021) where social ties have indirect effect towards the continuation usage of mobile payment in Indonesia. The users' behavioural intention towards the use of mobile wallet applications in Kuwait is also seen to have no significant relationship with social influence (Rabaa'i, 2023). Given the past studies research by Singh et al. (2020), Urus et al. (2022b), Handarkho et al. (2021) and Rabaa'i (2023) ranging from positive effects to negative effects to no observable influence, it is important to further investigate whether social influence plays a significant role in shaping Gen Z's adoption of AI tools in digital investment platforms.

2.2.3 Perceived Usefulness (PU)

The degree to which a person thinks that utilising a particular system will likely help them accomplish their objectives or perform better at work is known as perceived usefulness (Malik & Annuar, 2021). In the context of financial technology, it captures the extent to which users perceive that such AI tools would improve their investment decision-making in terms of accuracy, efficiency, and effectiveness. With integrated AI, digital investment platforms may significantly enhance investors' investment outcomes effectively and efficiently.

Digital investment platforms integrated with AI provide advanced functionalities such as robo-advisory services, real-time data, and market sentiment analysis. These capabilities enable investors to access large volumes of data, identify investment opportunities, and respond faster to market fluctuations. According to Shuo (2023), application of AI supports quantitative researchers in quantitative investment by shortening the development cycle of quantitative investment model and reducing the loading time to improve the strategy execution. AI tools such as robo-advisors are not only easy to access and cost effective but also competitive in investment performance, lowering entry barriers for retail investors and bringing significant advancement (Tao, 2021; Syed & Janamolla, 2024). AI thus not only assisted investors to achieve their financial goals but also takes them shorter time, proving both AI's effectiveness and efficiency which are attractive to investors.

Prior research conducted by Prastiawan et al (2021), Siagan (2022), and Ling (2024) have shown that perceived usefulness plays a crucial role in driving users' intention in adopting the financial technology. According to Jadil et al. (2021), performance expectancy is crucial to shape behavioural intentions. Investors are more likely to adopt technology that prioritizes performance to enhance their investment return. Investors may be more inclined to use digital investment platforms if they perceive that AI integrated in the platforms is able to help them make better investment decisions in order to generate higher return by utilizing functionalities of AI. Generative artificial intelligence demonstrates usefulness by enabling data analysis, predictive analytics, and portfolio maximization (Ray, 2023; Ahmad & Mokal, 2024). AI algorithms improve predictive accuracy by up to 90% with shorter response time in volatile market (Arifian et al, 2024). These benefits demonstrate why investors may perceive AI as useful for achieving higher return, subsequently adopting digital investment platforms integrated with AI. Furthermore, the speed of AI-enabled decision-making can give investors a competitive advantage over those relying on manual analysis, proving AI's usefulness for investors with weaker financial background. In support of this, a further study conducted in Germany found that the intention to use digital investment services may grow by 0.57% for every 1% increase in perceived usefulness (Seiler & Fanenbruck, 2021). These results highlight how technology adoption in the financial sector is influenced by perceived utility.

Nevertheless, a study conducted by Pramod et al. (2024) has found that perceived usefulness is insignificant for older people to adopt generative artificial intelligence. The elderly demographic in this study might have different priorities than younger people. Similarly, Shahzad et al. (2022) found that perceived usefulness was not a significant factor influencing other fintech adoption, online loan aggregator. In contrast, another research conducted by Lina et al. (2021) found that millennial investment intentions are affected by perceived usefulness. For Gen Z investors, perceived usefulness might be more influential as they value performance more compared to elderly users. As Gen Z are more familiar with digital ecosystems and comfort with algorithmic decision-making, they are more likely to view AI as a natural extension of their investment toolkit, reinforcing its role as a critical adoption factor. In present research, perceived usefulness expected to play an important role in influencing the adoption of digital investment platforms, as Gen Z investors are generally driven by the desire for better outcomes.

2.2.4 Perceived Ease of Use (PEOU)

Perceived Ease of Use (PEOU) of AI-driven tools that support Gen Z's investment decisions is considered as a significant factor that affecting the performance expectancy of digital investment platforms. According to Bhattacherjee (2001), PEOU is the degree to which a person believes a system is easy to use and requires little mental effort. It also defined as the users are not requiring any additional skills in using new technology. As Chong et al. (2019) highlighted, platforms designed with user-friendly interfaces and clear instructions can significantly ease the process of conducting online. In this context, AI technologies can enhance investment decision-making by simplifying complex financial data, providing real-time insights, and recommendations tailored investment advice with minimal user input.

PEOU is conceptually aligned with effort expectancy. It is stated that trust in financial robo-advisors (FRAs) is positively correlated with effort expectancy (Nourallah, 2023). The trust in automated services is significantly influenced by the task difficulty and system complexity. Hence, the FRAs perceived as an user-friendly and low effort are more likely to be utilised by young retail investors (YRIs). Arifa (2025) also found that a user-friendly system reduces the effort and time investment needed, increasing the likelihood of adoption. Wandhe (2024) highlights that Gen Z have highly focus and expects that the mobile digital platforms can be fast, intuitive, and user-friendly. Seiler and Fanebruck (2021) shows that perceived ease of use is positively related to the usage intentions of digital investment platforms. This indicates that when the users perceive the platform to be easier to use, their intention to apply it will increase significantly. Moreover, Istiqomah and Alfansi (2024) explained that the relationship between perceived ease of use (PEOU) and actual use of AI influenced by user's attitudes towards using the technology. When users feel that AI technology is easy to use and have positive attitude on it, they are more likely to adopt it.

Furthermore, PEOU has a broader role within the Islamic fintech industry, supporting user adoption and engagement. Based on the article of Kok and Siripipatthanakul (2023), AI has significant impact the conventional and Islamic finance industries in Malaysia. It improves the business models and ensures the transparency and efficiency of the products on Shariah compliance. Investment Account Platform (IAP) launched have combines both Islamic banks' credit valuation and advanced technology to help retail investors allocating their funds quickly and easily. According to Syed Musa et al. (2025), AI-powered robo-advisory services use AI algorithms to provide automated and tailored investment advice to Islamic investors. They can exclude and filter out those non-compliant investment securities with minimal research and effort. However, PEOU do not have significant positive impact with the adoption of Islamic fintech (Hasyim et al., 2023). This means that even there is improvement in ease of understanding, mastery, and usage, it will only contribute little or no impact on the adoption of Islamic fintech. This results also similar to the previous study by Sulaeman (2021). It highlights that perceived ease of use has no effect to Shariah fintech users during

COVID-19 pandemic. In this research, only conventional fintech products are included, as the study focuses specifically on this sector. The scope of fintech is extensive, and therefore Islamic fintech products are excluded to maintain a targeted research focus.

Rahadi et al. (2021) discovered, however, that the user's intention to embrace digital platforms is more mediated by trust than by perceived ease of use (PEOU). Zamzami (2021) shows that a trustworthy system will increase the usage of digital investment platforms. Kasemharuethaisuk and Samanchuen (2023) also stated that a convenient and trustworthy platform can increase the technology acceptance for mutual fund users. This indicates that when users are already familiar with digital interface, perceived ease of use is seen as a basic requirement rather than a key reason for adoption. Similarly, Khati et al. (2024) shows that other factors such as user attitude may carry more weight in impacting the adoption decisions in blockchain-based system. In contrast, study of Asante and Baafi (2022) mentioned institutional-based trust is not significant impact on the adoption of digital platforms due to lack of awareness of security aspects. In robo-advisory sector, trust of individual investors also has negative effect on the willingness to adoption the platforms. (Mittal, 2025). Therefore, trust was not included in the research due to its inherently subjective nature, as each individual has their own requirements and criteria for understanding the trust, making it challenging to measure consistently across participants.

2.2.5 Hedonic Motivation (HM)

The willingness to start behaviours or acts that increase the good experience (pleasure) and lessen the negative experience (pain) is known as hedonic motivation (Polisetty et al., 2024). According to Hartelina et al. (2021), hedonic motivation is seen to have a strong positive impact towards the intention of using online learning applications in an Indonesian study. This study is considered relevant to the present research as online learning applications and digital investment platforms share similar characteristics such as their user-interactive and online platform. Therefore, it acts as a useful basis for examining whether hedonic motivation similarly affects users' inclination in utilising digital investment platforms. Additionally, Nikolopoulou et al. (2021) have demonstrated that secondary school teachers' behavioural intention to adopt mobile technology is positively influenced by hedonic motivation. Since hedonic motivation has been proven to be a positive factor in mobile learning adoption, it develops further into whether hedonic motivation affects the Gen Z's users to engage with digital investment platforms.

In this era of globalisation, hedonic motivation is a crucial factor in predicting the intention and use of various digital platforms such as digital banking, P2P lending platforms and more. The feeling of enjoyment draws the user's intention to use technology and shift from commercial bank to digital banks (Anggraeni et al., 2021). Emotional factors such as joy and gadget attachment influenced the intent of investors in engaging with P2P lending platforms (Ramachandran et al., 2024). Hedonic motivation, in relation with the UTAUT hypothesis, is found to have the second-largest direct influence towards the intention of using and the intention of sticking with digital wallet (Sudirjo et al., 2023). Users who are happy using digital investment platforms increases the feeling of pleasure which in turn increases the hedonic motivation. Additional features such as the use of digital investment tools like robo-advisors, chat assistance, financial information notifications tend to attribute to increasing hedonic motivation and developing investment interest within users and the adoption of users to shift to a new platform and continue using the platform (Rahmantari et al., 2024). These features are perceived as internal motivation which influences behavioural intention of users in adopting digital investment platforms (Fernando et al., 2021). While this current research does not look into platforms such as P2P lending platforms, digital banks and digital wallets, it is relevant to include the past study by Anggraeni et al. (2021), Ramachandran et al. (2024) and Sudirjo et al. (2023) to relate the similarities between the platforms aforementioned with the new emerging Fintech service, digital investment platform.

Gamification is also another way of influencing hedonic motivation by increasing the satisfaction of users. When social influences like sentiments and happiness are higher, users are more likely to intend to adopt gamified mobile wallets (Yang et al., 2023; Lee et al., 2022). Relate back to this research, gamification such as stock market stimulation game is found to attract the attention and participation of young and inexperienced investors (Şenol & Onay, 2023). Therefore, it is worth investigating whether similar gamification elements that are possibly found in digital investment platform can enhance hedonic motivation which in turn increases the adoption of digital investment platforms among Gen Z investors.

Hedonic motivation is observed to have no effect on the intention to utilise Fintech services, despite being a substantial component determining behavioural intention (Amnas et al., 2023). Similarly, Nugroho and Karim (2023) found that there is no significant impact brought by hedonic motivation towards the adoption of OVO, an e-wallet in Indonesia. This is further backed up with research which show hedonic motivation is not considered as a factor in enhancing the technology acceptance of kiosks of Quick Service Restaurants (QSR) in Korea, and also the adoption of mobile payment platforms in India (Seo, 2020; Gupta & Arora, 2020). According to these past research, hedonic motivation is seen not as a contributing factor towards the adoption of technologies, which links with the present research in determining if hedonic motivation affects the engagement of Gen Z's in digital investment platforms.

2.2.6 Artificial Intelligence (AI)

Artificial Intelligence is the ability of computer systems to perform tasks that require human intelligence. This includes learning, problem-solving, and decision making. In the context of digital investment platforms, AI plays a critical role in enhancing system capabilities by incorporating features like robo-advisory and predictive analytics. These features can improve users' perception of system performance, which aligns with the concept of performance expectancy.

Prior research found that AI-driven functionalities significantly improve users' perceived usefulness and efficiency of financial technologies. Study revealed that explainable artificial intelligence can improve human decision-making (Alufaisan et al., 2021). Study from Samara et al. (2024) demonstrated that integrating AI into a business environment improves the quality and accuracy. Similarly, study from Fonseca et al. (2024) also found that AI can enhance strategic decision-making within healthcare context.

In the fintech context, Kamuangu (2024) stated that AI possibly enhance efficiency and personalisation. These advancements enhance users' perceptions of how well digital investment platforms perform. As AI-driven features become more sophisticated, users may perceive such platforms as effective in their investment decisions. Furthermore, a study on major banks in Pakistan found that AI and fintech integration significantly improve financial performance (Iqbal & Fikri, 2025). The findings suggest that AI-driven systems enhance efficiency and service quality, which can positively shape users' expectations of platform performance. This supports the notion that AI adoption increases performance expectancy in digital financial platforms.

Malaysia is an emerging market where digital investment platforms are still evolving. AI serves as a key enabler in bridging the gap between complex financial analysis and user accessibility. Thus, it is reasonable to expect that AI has a significant positive influence on performance expectancy.

2.2.7 Mediating Role of Artificial Intelligence

Artificial Intelligence (AI) has been a transformative force in finance industry in recent years. The role of AI in reshaping the investment behaviour of individuals is significant through the ability of AI in recognising the pattern of human investment behaviour using AI-driven algorithms (Das & Das, 2025). By integrating AI in the financial sector, positive impacts such as enhanced decision-making processes, portfolio rebalancing, and advancements in digital brokerage and algorithmic trading can be observed (Rehman et al, 2024; Orgeldinger, 2024; Challa, 2025).

Apart from that, AI is seen as a tool in enhancing market presence and a measure to launch new innovative solutions (Chen & Chen, 2024). This is due to the various functions that can be performed by AI associated with the human intelligence such as reasoning, perceiving, and problem-solving while extracting insights, handling large volumes of data, and inferencing methods (Varghese et al., 2024). Such benefit not only limits within the conventional financial sector but also the Islamic financial sector. Pathan et al. (2022) states that AI offers many advantages to the applications in Pakistan due to its conformation to Shari'ah.

Nevertheless, AI has become a pivotal component of digital investment platforms in this era of digitalisation, reshaping how investment decisions are made, executed, and monitored. When AI is used to estimate an investment's fair value, investors make smaller additional investments when the fair value is anticipated to be positive and withdraw smaller investments when the fair value is anticipated to be negative (Downen et al, 2024). As compared to human staff usage, the usage of AI in investment analysing results in more rational decisions by investors due to the trust and reliability of AI. The implementation of Robo-Advisor framework while integrating Deep Learning (DL), Reinforcement Learning (RL), and Natural Language Processing (NLP) has yield significant advancements in personalised investment management (Ablazov et al., 2024). This is said as it leverages the ability of AI in analysing market trends and optimising portfolio management, enhancing and surpassing traditional investment strategies and existing Robo-Advisors.

This research determines the role of AI in mediating the independent variables in affecting the dependent variable. While past research rarely investigates such relationships, it is worth comparing existing research to identify gaps in the study. Yi and Choi (2023) found that AI services increased the helpfulness, greater satisfaction with ICT experiences, and higher expectations for AI, which all contribute to the intention of accepting AI in products and services in Korea. By referring to past research as a foundation, similar understandings can be applied in the context of digital investment platforms. This approach enables this study research in determining whether AI plays a significant mediating role between social influence, perceived usefulness, perceived ease of use, hedonic motivation, and the performance expectancy of digital investment platform.

In terms of identifying the mediating role of AI between social influence and the performance expectancy of digital investment platform, the element of trust and confidence towards AI tools is worth investigating. Trust is a key in linking the performance expectancy of a tool and the adoption of a new technology specifically when involving AI-specific characteristics in various fields such as the healthcare sector (Cheng et al., 2022; Liu & Tao, 2022). Li (2025) found that social influence increases the inclination of individuals adopting AI-Generated Content (AIGC) in the design field, the presence of perceived risks may impose constraints on their willingness to adopt the technology. Similarly, while social influence can encourage adoption, the enhancement of AI tools in providing data-driven support boosts the perceived performance expectancy of digital investment platforms thus influencing the utilization of digital investment platforms among Gen Z.

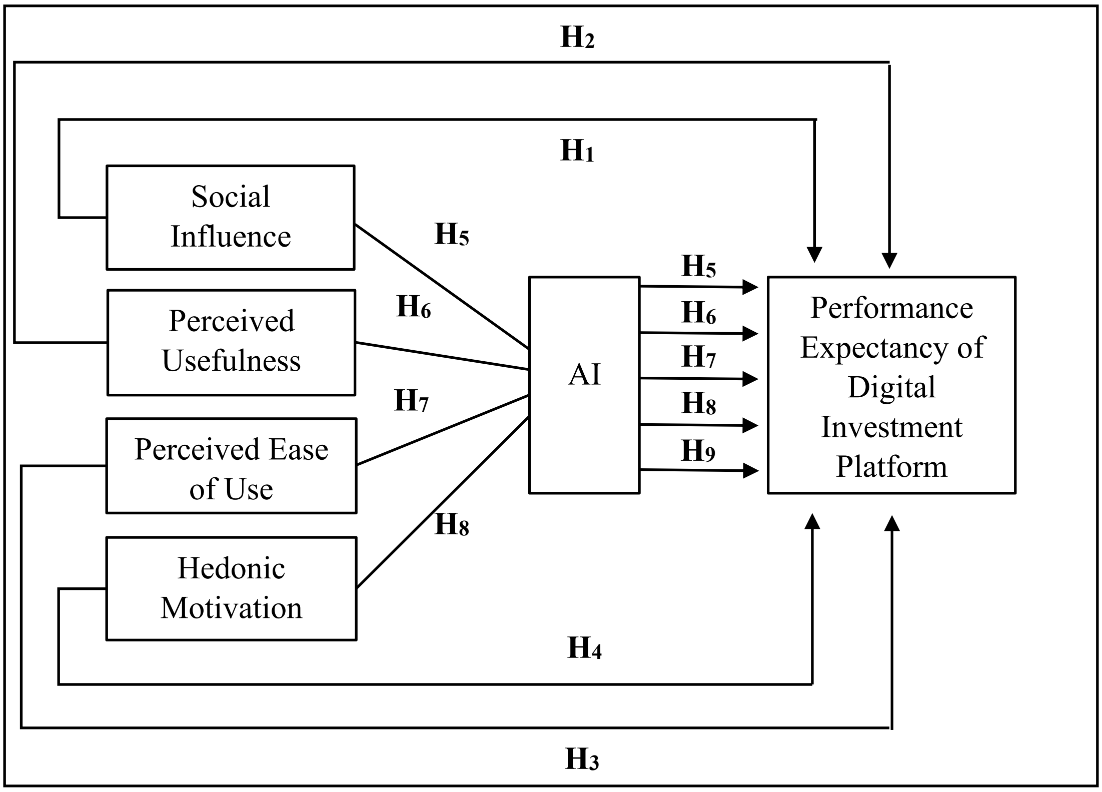
The mediating role of AI in the relationship between perceived usefulness and the performance expectancy of digital investment platforms can be determined through the enhancement of usefulness perception and the improved performance brought by the platform. The integration of AI in the financial advisory services allows financial companies to offer more personalised and efficient investment services to their clients (Huang et al., 2024a). While perceived usefulness is determined whether it is significantly related to the performance expectancy of digital investment platforms, the integration and the mediating role of AI in the financial sector is also studied in this research.

Besides, the role of AI in mediating the relationship between perceived ease of use and the performance expectancy of digital investment platforms can be seen in terms of the reduction of complexity of the platform which results in a higher performance expectancy. As mentioned by Pramod and Rahman (2022), the ease of use of AI tool is of paramount importance in the determination of the intention of students in making financial investment decisions. AI plays a predominant role in structuring a better ease of usage among investors in the utilisation of Robo-Advisory services (Ramesh et al., 2023). Thus, it is worth investigating whether AI mediates the relationship between perceived ease of use and the performance expectancy of digital investment platforms among Gen Z in this research.

Lastly, the mediating role of AI between the relationship of hedonic motivation and performance expectancy of digital investment platforms can be identified through more engaging experiences for users. AI is a suitable tool in providing personalised services which offer a satisfactory service to users by providing financial advice which meets the users' needs (Singh & Kumar, 2024). Au et al. (2021) found that young investors are more likely to use robo-advisory services as it provides higher satisfactory in Germany. A higher satisfaction of using digital investment platforms attracts the adoption of new technology, whereas the mediating effect of AI in strengthening this relationship is studied in this research.

2.3 Conceptual Framework

Figure 2.3: Conceptual Framework



Source: Developed for Study

The conceptual framework of the study involves two theories which are Technology Acceptance Model (TAM) from Davis (1989) and AI Decision Use Acceptance (AIDUA) from Gursoy et al. (2019). These models can help to measure and explain the cognitive factors that influence the adoption of digital investment platform by Gen Z with the help of AI tools. From the figure above, the framework identifies the relationship between the four independent variables, which are Social Influence (SI), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Hedonic Motivation (HM) to the dependent variables, Performance Expectancy of Digital Investment Platform (PE). Within this framework, AI serves as the mediating variable. This highlighted that performance expectancy is not only influenced by belief or attitudes, but also by actual experience of using AI tools. Performance expectancy refers to the outcome of using AI instruments in improving the quality, speed, and accuracy of investment decisions.

Among the independent variables, SI is applied as it can capture and include the external pressures or peer motivation that may impact on application of AI tools of Gen Z. Apart from that, it also can measure how friends, social media influencers, or any community influence technology adoption in investment decision, particularly in younger generations (Ajzen, 1991). The research also uses PU and PEOU in TAM as they can consistently measure the degree of individuals in adopting a new technology. Both are able to assess to whether Gen Z will believe that AI tools can help them to improve the investment decision-making (Venkatesh & Davis, 2000). Moreover, HM is the enjoyment or fun when using AI tools. In some cases, Gen Z not just focus on the function of AI or the outcome performance, but they also wish to enjoy the process and involve emotional engagement.

The conceptual framework is developed by incorporation various recommendations through limitations of past research. In addition, Rahadi et al. (2021) suggested adding further variables to the framework. Since there are similarities between the adoption of electronic payment devices and the adoption of digital investment platforms due to their characteristics of Fintech services, additional factor such as hedonic motivation is added in this current research to further investigate the factors affecting the performance expectancy and adoption of digital investment platforms. Similarly, Anggraeni et al. (2021) also proposed the addition of other constructs relevant to the adoption of digital platforms apart from the UTAUT (Unified Theory of Acceptance and Use of Technology) model. In this research, a more recent theory, AIDUA model is considered. Rahmantari et al. (2024) also proposed the focus of user generations more specifically such as millennials or Gen Z in the context of digital investment. Therefore, the current study focuses on Gen Z's adoption of digital investment platforms.

2.4 Hypothesis Development

2.4.1 Social Influence

The degree to which a person's decision is influenced by the views of those in their social circle is known as social influence. The adoption of technologies, including apps, technologies, and digital platforms, is thought to be significantly influenced by social impact (Nguyen, 2022; Fox et al., 2021; Nasution et al., 2022; Joa & Magsamen-Conrad, 2022). In the financial sector, Fedorko et al. (2021) found that social influence has a positive effect on the performance expectancy of internet banking. Almarashdeh et al. (2021), who claim that social influence has a direct positive significant influence on the behavioural intention to use bitcoins, corroborate this claim. Therefore, the hypothesis of social influence having a positive relationship between social influence and performance expectancy of digital investment platform is expected.

H_1: There is a significant relationship between social influence and performance expectancy of digital investment platforms.

2.4.2 Perceived Usefulness

Perceived usefulness has long been recognised as a key determinant of technology adoption and user performance expectations. A higher level of perceived usefulness of digital investment platforms can lead to users' higher expectations of greater efficiency, accuracy, and informed decision-making when managing investments.

Performance expectancy is the primary predictor of behavioural intention to use technology. Empirical studies have also shown this positive relationship. According to Antonio et al. (2024), the perceived usefulness of mobile P2P payments has a significant impact on user adoption. This is consistent with the UTAUT framework’s concept of performance expectancy, which states that people are more likely to adopt technology when they think it will improve their performance. In financial context, perceived usefulness was found significant to predict users’ intention to adopt online banking (Ander et al., 2021; Nayanajith et al., 2021). Oyman et al. (2022) found that users are likely to use the augmented reality-supported mobile app when it is useful. Additionally, online consumer behaviour is also positively influenced by perceived usefulness (Soares et al., 2023). In the context of investment decision-making, if the users perceived that the platforms are useful for delivering accurate financial information, they are more likely to anticipate better investment outcomes, thereby elevating their performance expectancy.

H_2: There is a significant relationship between perceived usefulness and performance expectancy of digital investment platforms.

2.4.3 Perceived Ease of Use

The degree to which people think using a platform involves little effort is known as perceived ease of use. They are more likely to adopt it if it provides benefits to their performance. According to a study by Sembiring (2022), preferred mutual fund investing platforms have been positively impacted by perceived ease of use. This will bring the same impact to performance expectancy, as majority of respondents agreed in this context. Furthermore, Su and Li (2021) demonstrate that one of the elements that favourably affects performance anticipation is perceived application ease. The article of Amelia (2024) indicates a direct positive link between ease of use and expected performance improvements in digital finance sector. According to Rahim et al. (2022) and Sabir et al. (2023), performance expectancy in Islamic fintech and digital investing platforms is directly and favourably impacted by perceived ease of use.

H$_3$: There is a significant relationship between perceived ease of use and performance expectancy of digital investment platforms.

2.4.4 Hedonic Motivation

The degree of pleasure, happiness, and fun derived from utilizing a specific technology is referred to as hedonic motivation. Hedonic motivation is positively influencing the behavioural intentions of adopting Fintech such as robo-advisor in Indonesia (Zhafira et al., 2025). In a similar vein, Anggraeni et al. (2021) discovered a favourable correlation between the intention to use digital banking and hedonic motivation. More specifically, hedonic motivation is also found to positively influence the behaviour intention of using Fintech investment management, relatable to the current research (Saraswati et al., 2023). This statement is supported by Prasarry et al. (2023) which shows a positive relationship between hedonic motivation and the intention of Gen Y and Z in using investment applications. Therefore, the hypothesis of hedonic motivation having a positive relationship between social influence and performance expectancy of digital investment platform is expected.

H$_4$: There is a significant relationship between hedonic motivation and performance expectancy of digital investment platforms.

2.4.5 Mediating Role of AI

By enabling more precise forecasts, automated decision-making, and tailored investment advice, AI has revolutionised the financial industry. However, the potential role of AI as a mediator remains underexplored from past research. By mediating the relationship between the dependent variable performance expectancy of digital investment platforms and independent variables social influence, perceived usefulness, perceived ease of use, and hedonic motivation, AI enhances the user's perception of the digital investment platform capabilities which ultimately influences the decision of users to adopt digital investment platforms.

It is found by Bai and Yang (2025) that social influence significantly enhances the performance expectancy, enhancing the usage intention of Artificial Intelligence Generated Content (AIGC). Alhwaiti (2023) found similar results stating the positive relationship between social influence towards the performance expectancy and adoption of AI. Social influence has positively influenced the performance expectancy of AI and the significant effect of AI links between the performance expectancy and use of technology (Jain et al., 2022). Hence, we hypothesise:

H_5: AI significantly mediates the relationship between social influence and the performance expectancy of digital investment platforms.

AI features can enhance the relationship between perceived usefulness and performance expectancy by amplifying the value users derive from digital platforms. AI can easily perform certain tasks as compared to traditional methods. Artificial intelligence tools are increasingly capable of processing complex datasets, uncovering market patterns, and delivering customised investment recommendations that go beyond traditional analysis methods (Fatouros et al., 2024). This indicates that AI can improve decision efficiency, strengthening users' perception of usefulness. Prior research indicates that the use of AI-powered robo-advisors positively influences users' trust and adoption of digital investment platforms (Zhu et al., 2024; Syed & Janamolla, 2024). AI tools are said to be more useful than traditional methods, leading to investors' perception that digital investment platforms are useful. Furthermore, AI can also significantly assist in quantitative investment strategy to achieve profit and risk control (Bi et al., 2024). According to Wang et al. (2023), behavioural intention in using a new technology has a beneficial impact on its actual use, and perceived usefulness has a positive effect on that intention. Thus, in digital investment context, AI facilitates the realisation of perceived benefits, making it a critical factor in strengthening the link between perceived usefulness and performance expectancy. Hence, we hypothesise:

H_6: AI significantly mediates the relationship between perceived usefulness and the performance expectancy of digital investment platforms.

Users will embrace technology or services if they find the features of the technology to be user-friendly. Users will feel relieved when using technology requires little to no effort. In digital banking and investment platforms, perceived ease of use not only reduce the effort needed, but also strength performance expectancy, especially mediating through AI tools. Mei et al. (2024) shows that user-friendly design and interaction with AI enhance both ease of use and perceived system performance in sustainable banking industry. Users who considered AI products easy to use were more likely to utilise them in the future, especially if they trusted AI (Ikhsan et al., 2024). Similarly, in personal financial planning, individuals with higher technology readiness found AI tools simpler to use. AI can provide customised financial insights and advice, enhancing their performance expectancy (Osman & Mohamad, 2024). In robo-advisory adoption, perceived ease of use has enhanced user's attitudes and intentions to use the digital platforms, particularly when trust is present, which can lead to good performance expectancy (Singh & Kumar, 2024). Performance expectancy positively influences the adoption of digital AI technology, and it is seen that users are more willing to use technology if it performs better than expected (Kosasi et al., 2023). Hence, we hypothesise:

H_7: AI significantly mediates the relationship between perceived ease of use and the performance expectancy of digital investment platforms.

The pleasure or happiness that comes from utilising a technology is known as hedonic motivation. Upadhyay et al. (2022) mentioned the positive impact of hedonic motivation towards the entrepreneur's acceptance intention of AI. This statement is supported by Huang et al. (2024b) who found that hedonic motivation is one of the top three constructs which positively affects the behavioural intention of the acceptance of AI. The behavioural intention, positively influenced by user satisfaction maximises the adoption of AI technology (Jang et al., 2024). It is also found that the differences in expectations about AI performances where users expect higher performance, but the results are lower than expected affects the intention the usage of AI technologies (Hong, 2021). Hence, we hypothesise:

H_8: AI significantly mediates the relationship between hedonic motivation and the performance expectancy of digital investment platforms.

2.4.6 Artificial Intelligence

Artificial Intelligence is the use of advanced algorithms and machine learning to enhance decision-making processes. In the context of digital investment platforms, AI-driven features can improve the efficiency of investment decisions. To illustrate, AI technologies significantly enhance system performance and user outcomes in mobile banking and personal finance (Kiruthiga, 2025; Schrank, 2025). More specifically, FinTech employed AI to offer personalised financial recommendations, hence performance expectancy is critically influencing FinTech adoption including digital investment platforms (Senyo & Osabutey, 2020; Amnas et al., 2023). When users perceive that AI can enhance the effectiveness of digital investment platforms, they are more likely to build higher expectations. Therefore, AI plays a crucial role in shaping users' perception of how well digital investment platforms can support their investment goals.

H_9: There is a significant relationship between AI and performance expectancy of digital investment platforms.

2.5 Conclusion

In this chapter, the theoretical framework which include Technology Acceptance Model (TAM) and AI Device Use Acceptance (AIDUA) are explained. Besides, the independent variables which are social influence (SI), perceived usefulness (PU), perceived ease of use (PEOU), and hedonic motivation (HM), and dependent variable, performance expectancy of digital investment platforms are also discussed based on relevant past studies. In the next chapter will cover the research methodology.

CHAPTER 3: METHODOLOGY

3.0 Introduction

Chapter 3 outlines the research methods employed to accomplish the study's goals. The research design, which outlines the design selection, comes first. The sampling design, which includes the target population, sampling techniques, and sample size determination, is then explained after the data collection process. The next section explains the research instrument such as the design of questionnaire, pre-test, and pilot test. Then, the construct measurement will be discussed which highlights the scale of measurement and use of Likert scales. Subsequently, the data processing procedures are explained. Lastly, the proposed data analysis tool where both descriptive and inferential statistical methods are introduced to analyse the collected data.

3.1 Research Design

The broad framework that outlines the strategy for carrying out the research is referred to as research design. In order to accomplish the predefined research objectives, it guides the process of collecting, computing, and analysing data. There are three different kinds of study designs: mixed, qualitative, and quantitative.

A quantitative approach was chosen for this research as this research relies on numerical data collected through structured questionnaires and aims to statistically test and examine the connection between the dependent and independent variables through the mediating role of AI. This method allows the use of statistical techniques such as the PLS-SEM to examine the hypothesised relationship and generate research findings that are objective and generalisable.

3.1.1 Descriptive Research

A descriptive research design was used in this research. The study method that methodically characterizes a population, circumstance, or phenomena in order to accurately depict the traits, behaviours, and patterns within a particular group is known as descriptive research. The focus of this research was to describe and analyse the perceptions, attitudes, and behaviours of Gen Z investors in Malaysia in perceiving and adopting new technologies such as digital investment platforms. This descriptive research identified the trends, relationships, and patterns among independent variables and dependent variable. Thus, it provided a comprehensive overview of how Gen Z investors' investment decisions are influenced through the mediation of AI.

3.2 Data Collection Method

One of the most crucial aspects of a research project is gathering data. It is utilised to assess the research's findings and refers to the methodical procedure of obtaining data from research variables.

3.2.1 Primary Data

The word 'datum' refers to the singular form of the word 'data'. Methods such as surveys, questionnaires or research studies are used to collect information which turns into useful data. Since primary data represents the actual circumstances or status of the targeted group, it was gathered for this study. It is the original information that the researcher has gathered using a variety of methods, including surveys, questionnaires, interviews, and observations. Questionnaires were sent to the targeted population for this process. After collecting primary data, the original data is obtained to measure the connection between the dependent and independent variables through the mediating role of Artificial Intelligence (AI).

3.3 Sampling Design

3.3.1 Target Population of Study

Generation Z individuals in Malaysia made up the study’s target group. They are either current users of digital investment platforms or potential adopters. According to Priporas et al. (2017), this population is digitally native to AI features such as robo-advisory and chatbots, so they are appropriate for studying performance expectancy of AI tools in financial investment. Gen Z represents roughly 29% of the population in Malaysia and is highly active online, spending around eight hours per day on the internet (Tjiptono et al., 2020). Hence, Gen Z will be the primary target population.

3.3.2 Sampling Location

Present study targeted the Generation Z investors in Malaysia. As digital investment platforms are accessible nationwide, Malaysia was chosen.

3.3.3 Sampling Elements

Non-probability purposive sampling was the method of sampling employed in this research study. The samples were selected from Generation Z individuals in Malaysia who have experience with or intention to use digital investment platforms with AI features.

3.3.4 Sampling Techniques

In present study, data was collected using a questionnaire designed for Generation Z individuals in Malaysia who are currently using or intend to use digital investment platforms with AI features. Applying purposive sampling technique can ensure that only respondents who fit these criteria were included in the study. This method is comparable to that used by Priporas et al. (2017) to examine the expectations of Generation Z in digital environments using purposive sampling.

3.3.5 Sample Size

A sample is a subset of people chosen for research from a broader population. In research, a suitable sample size is also essential. Determining an optimal sample size is essential to minimize sampling error and ensure reliability of the findings. Several methods such as Cochran's formula, statistical power analysis, and more are commonly used in deciding sample size (Nanjundeswaraswamy & Divakar, 2021). In order to create a better decision model, Krejcie and Morgan (1970) suggested that the sample size approximately to be based on population.

Table 3.1: *Sample Size Range*

Population Range	Approximate Sample Size
10,000	370
15,000	375
30,000	379
50,000	381
75,000	382
100,000	384

Source: Krejcie, R. V., & Morgan, D. W. (1970)

When the studies are applying structural equation modelling (SEM), the sample should be large enough to ensure stable parameter estimates and allow mediation analysis (Hair et al., 2022). According to Department of Statistics Malaysia (2024), Malaysia has a total of 34.1 million population in 2024. Hence, the population for Gen Z will be approximately 9.9 million. In present research, 384 respondents will be required. An approximate 0.003879% of Gen Z respondents are included from the population of Malaysia.

3.4 Research Instrument

3.4.1 Design of Questionnaires

In this study, questionnaire was applied to obtain the data from Gen Z. A questionnaire is thought to be the best method for gathering data for this study since it is excellent for gathering information from people who are dispersed throughout a large area and difficult to reach in person. It consists of a structured set of questions that presented to the respondents, accomplishing by the clear instructions outlining the sequence of questions and criteria for selecting them. The main functions of a questionnaire are to record responses, enable efficient data processing, and supply the organised data necessary for the assessment of both quantitative and qualitative data. Questionnaire are separated to two different categories which include open and closed-ended questions. Closed-ended question offers a fixed set of choices to the respondents, while open-ended question allows the respondents to fill in their own answers.

There are three sections of questionnaire: Section A, B, C. Section A is related to demographic variables of the responders. Section B comprises inquiries concerning the response variables, which is the digital investment platforms. Section C contains questions concerning the factors that influence the dependent variable and AI as a mediating role.

3.4.2 Pre-Test

Before the questionnaire was given to Malaysia's Gen Z, all of the independent and dependent variables were examined. After the questionnaire has been developed, a pre-test will be given to a small sample of respondents to confirm its validity and reliability. This process involves the discussion between team members of this research with the group's supervisor.

3.4.3 Pilot Test

Pilot test was conducted to assess the viability of methods and procedures in large-scale of research. There are two portions that must be used in the pilot study. Sample size requirements for pilot studies are among the statistical and design considerations covered in Section 2. Pilot testing is crucial as it tests the research design methodologies to determine the adequacy of the procedures and methods used in the study. Thirty respondents from Malaysia’s Gen Z demographic participated in the study’s pilot test and were invited to voluntarily fill out the questionnaire. After completion, the input was thoroughly examined, and small changes were made to the questionnaire to make it clearer and less redundant.

3.5 Construct Measurement

The process of determining how the variables in research are measured and evaluated using observable indicators is known as construct measurement.

3.5.1 Scale of Measurement

The classification, quantification, and interpretation of variables in statistical analysis are determined by the scale of measurement.

3.5.1.1 Nominal Scale

Qualities that are named and lack mathematical features are represented by nominal scale data. For example, gender. Section A of this questionnaire, which mainly revolves around demographic questions is assessed using nominal scale.

3.5.1.2 Ordinal Scale

Ordinal scale involves the ranking of items, usually in a sequence. Apart from Section A, other sections in this questionnaire uses Likert Scale, which is considered as an ordinal scale.

3.5.2 Likert Scale

5-point Likert scale functions to capture responses of this questionnaire to obtain data. Likert scale design questions according to point scale. In order to determine how strongly respondents agree or disagree with a proposition, a 5-point or 7-point scale is typically employed. Using a 5-point Likert scale, the selection ranges from 1, which is indicated as “Strongly Disagree” to 5, which is “Strongly Agree”, with 3 being “Neither Agree nor Disagree”.

Table 3.2: *5-point Likert Scale*

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
1	2	3	4	5

Source: Alkharusi (2022)

3.5.3 Measurement Items for Questionnaire

Table 3.3: *Measurement Items for Questionnaire*

Dependent Variable		**Sources / Adapted from**
Performance Expectancy of Digital Investment Platform (PE)	PE1: Using digital investment platform would help me accomplish financial goals more quickly. PE2: I intend to keep using digital investment platform for making sustainable investment decisions. PE3: I believe that using digital investment platform would increase my productivity. PE4: I intend to use digital investment platform in the near future due to its performance.	Gan et al. (2021), Mohapatra et al. (2025), Nourallah (2023)

Independent Variable		**Sources / Adapted from**
Social Influence (SI)	SI1: People who are important and who can influence my behaviour think that I should use digital investment platform. SI2: Financial experts and mentors I follow encourage the use of digital investment platforms. SI3: My peers believe that digital investment platforms is beneficial for making financial decisions. SI4: Most people in my social circle (e.g., friends, colleagues) use digital investment platforms to support their investment.	Gan et al. (2021), Nourallah (2023), Sergeeva et al. (2025), Gursoy et al. (2019)

Perceived Usefulness (PU)	PU1: The digital investment platform can improve the overall performance of my sustainable investment portfolio. PU2: I believe that the digital investment platform provides useful insights into sustainable investment opportunities. PU3: The digital investment platform is useful in aligning my investment strategy with sustainability. PU4: Using digital investment platform would improve my investment performance and productivity.	Mohapatra et al. (2025), Davis (1989)
Perceived Ease of Use (PEOU)	PEOU1: I would find it easy to get digital investment platform to do what I want it to do. PEOU2: I would find digital investment platform to be flexible to interact with. PEOU3: It would be easy for me to become skilful at using digital investment platform. PEOU4: I would find digital investment platform easy to use.	Davis (1989)
Hedonic Motivation (HM)	HM1: Using digital investment platform is fun. HM2: Using digital investment platform is enjoyable. HM3: I enjoy using digital investment platforms because they make my investment experience more fun and engaging. HM4: I find it exciting to interact with digital investment platforms as it adds an element of novelty to my investing experience.	Nourallah (2023), Sergeeva et al. (2025), Venkatesh et al. (2012)

Mediating Variable		Sources / Adapted from
AI	AI1: My general knowledge about AI is more than sufficient compared to many. AI2: Learning and implementing innovations in AI applications are a priority for me. AI3: I take pleasure in using artificial intelligence applications. AI4: Learning artificial intelligence applications is an easy task for me.	Yurt & Kasarci (2024)

3.6 Data Processing

Data processing is a critical step in transforming raw survey data into meaningful statistical analysis. This is to minimise the data's flaws, inconsistencies, and missing values, which lower the validity and dependability of the study's conclusions.

3.6.1 Data Checking

It involves examining the questionnaires that have been collected from respondents. The step of data checking serves to:

i. Verify that the questionnaires were completed and free from major errors
ii. Ensure that responses were logical and suitable for statistical analysis

For example, responses were checked for possible missing values in key sections of the questionnaire as partial questionnaires could distort the statistical analysis results. Moreover, attention will be given to identify response patterns such as "straight-lining", where the respondents select the same option throughout the questionnaire without proper consideration. Such response behaviour reduces the credibility of the data and might introduce biasness into the research findings. Besides, questionnaires with excessive missing data will be excluded at this stage as a measure to preserve the integrity and credibility of the data.

3.6.2 Data Editing

This process will be conducted to correct and refine the dataset. This step involves reviewing responses for possible inconsistencies and errors that may have arisen during the data collection stage. The step of data editing ensures that responses collected aligns with the research framework and scales. This step is crucial in enhancing data quality as small inconsistencies could affect the statistical reliability of the data analysis of the research.

3.6.3 Data Coding

As the research instrument utilises Likert scale, responses will be systematically converted into numerical values to allow for statistical processing. The scales will be coded to the following codes as per the Likert scale used by Alkharusi (2022). This conversion transforms subjective perceptions into quantifiable data, which makes analysing relationships among variables possible between dependent variable and independent variables. Apart from the Likert-scale items, demographic variables which includes age and gender are also coded numerically to facilitate group comparison in the analysis process. Thus, data coding serves as a bridge between raw qualitative inputs of respondents and the quantitative requirements of inferential analysis.

3.7 Proposed Data Analysis Tool

PLS-SEM, is a multivariate statistical technique which examines the relationship between variables. PLS-SEM is appropriate when complex models are analysed, sample size is limited, or when prediction is the focus of the research. PLS-SEM is applied in research to identify potential mediating effects. The current research explores the relationship between multiple independent variables and dependent variable with the role of AI as a mediator. Therefore, PLS-SEM is more efficient in handling such complex models and identifying potential mediating effects. The data will be analysed using SmartPLS 4.0, which is one of the most widely used software tools for PLS-SEM analysis.

3.7.1 Descriptive Analysis

The process of summarising data prior to PLS-SEM analysis is known as descriptive analysis. An overview of significant features of the sample that was gathered is given by the data summary. Frequency distributions, measurements of central tendency like mean, median, and mode, and measures of variability like range, minimum and maximum, and standard deviation are a few examples. Presenting a coherent and thorough outcome component is crucial. The present study used the descriptive analytic approach to summarise or categorise the respondents' demographic attributes, such as age, gender, education, etc.

3.7.2 Inferential Analysis

The ability to analyse sample-size data and extrapolate findings to the complete population is known as inferential analysis. Inferential analysis within PLSS-SEM is performed in two stages, which are the measurement model assessment and the structural model assessment.

3.7.2.1 Cronbach's Alpha

This is an estimator which tests the reliability in terms of internal consistency of the test score (Forero, 2024). The coefficient falls within the range of 0 to 1, with a higher value representing stronger internal consistency (Izah et al., 2023). Traditionally, a Cronbach's Alpha coefficient of 0.70 and above is an indicator for good internal consistency (Damianova et al., 2024; Kennedy, 2022) while other researchers like Izah at al. (2023) and Dalyanto et al. (2021) prefer values above 0.75 and 0.80.

Table 3.4: *Cronbach's Alpha Table*

Cronbach's Alpha	**Internal Consistency**
$0.90 \leq \alpha$	Excellent
$0.80 \leq \alpha < 0.90$	Good
$0.70 \leq \alpha < 0.80$	Acceptable
$0.60 \leq \alpha < 0.70$	Questionable
$0.50 \leq \alpha < 0.60$	Poor
$\alpha < 0.50$	Unacceptable

Source: Rungsinanont (2024)

3.7.2.2 Composite Reliability

Examining a construct's internal consistency and dependability is the goal of composite reliability. Composite reliability prioritises the items based on their individual dependability, accounting for different item factor loadings, whereas Cronbach's Alpha assumes that all things are equally reliable (Haji-Othman & Yusuff, 2022). The degree of dependability increases with composite reliability. A construct is denoted as good reliability if the composite reliability value is greater than 0.70 (Bakhtiar et al., 2021; Cheung et al., 2024; Haji-Othman & Yusuff, 2022). However, composite reliability values of more than 0.90 or 0.95 are potentially problematic as it signals redundant indicators which reduces construct validity (Hair et al., 2021).

3.7.2.3 Convergent Validity – Average Variance Extracted (AVE)

Average Variance Extracted (AVE) measures how much variance a concept captures relative to the amount of variance produced by measurement error (Santos & Cirillo, 2023). This metrics is used to evaluate the convergent validity of the construct (Hair et al., 2021). According to Shrestha (2021), an AVE of more than or equal to 0.50 confirms the convergent validity. This statement is supported by Hair et al. (2021) and Mohd Dzin and Lay (2021) who stated similar AVE acceptable value of 0.50.

3.7.2.4 Convergent Validity – Outer Loading

Outer loading refers to the regression coefficient between the observed variables (indicators) and the unobserved variables (latent constructs). It measures the strength between both indicators and latent constructs they represent (Subhaktiyasa, 2024). Outer loading values must meet a minimum threshold of 0.70 to be statistically significant (Deng et al., 2025). However, Fauzi (2022) and Subhaktiyasa (2024) stated the minimum threshold should be 0.708 due to the nature of the number 0.708 equals to 0.50 when being squared, which represents 50% variance. While there are conditions where outer loadings below the threshold level of 0.70 is accepted as long as it is above 0.60 (Shwedeh et al., 2024). It is also mentioned that indicators with an outer loading below 0.70 should be removed to improve AVE (Al-Marsomi & Al-Zwainy, 2023). Similarly, Chinyamurindi et al. (2023) removed all items with low outer loadings below 0.40.

3.7.2.5 Discriminant Validity – Heterotrait-Monotrait Ratio (HTMT)

According to Hair et al. (2021), Heterotrait-Monotrait Ratio (HTMT) is calculated by dividing the mean of the average correlations for the indicators measuring the same construct (monotrait-heteromethod correlations) by the mean of the indicator correlations across constructs (heterotrait-heteromethod correlations). Compared to more conventional methods like the Fornell-Larcker Criterion, it is a more efficient way to assess discriminant validity. The recommended HTMT ratio for each construct should be below 0.90, or 0.85 when constructs are conceptually more distinct (Cheung et al., 2023; Gelibolu & Mouloudj, 2025).

3.7.2.6 Path Coefficients

Path coefficient or path analysis is the measurement which examines the direct effect as well as indirect effect of independent variables on the dependent variable (Chaitanya et al., 2024). The range of path coefficients is between +1 or -1 (Awogbemi et al., 2022). Values nearer +1 suggest strong positive correlations, whereas values nearer -1 imply stronger negative relationships.

Table 3.5: *Path Coefficients Table*

Path Coefficient	**Relationship**
$P > 1.00$	Very High
$0.30 \leq P \leq 1.00$	High
$0.20 \leq P \leq 0.29$	Moderate
$0.10 \leq P \leq 0.19$	Low
$0.00 \leq P \leq 0.09$	Negligible

Source: Khan et al. (2022)

3.7.2.7 Bootstrapping

Bootstrapping methodology involves the process of creating bootstrap samples by repeating random sampling with replacement from the original sample. It is a technique in drawing conclusions based on the sample obtained to deduce the characteristics of the population. The significance testing relies on a bootstrapping procedure. Sarstedt and Moisescu (2024) ran bootstrapping for each model with the number of samples of 10,000 for bootstrapping technique.

3.7.2.8 Coefficient of Determination (R^2)

R^2 determines the proportion of variance in the dependent variable that can be explained by the independent variables. Higher R^2 values suggest a better fit of the model (Williams et al., 2024).

Table 3.6: *R^2 Table*

Coefficient of Determination	Level of Predictive Accuracy
$R^2 \geq 0.75$	Substantial
$0.50 \leq R^2 < 0.75$	Moderate
$0.25 \leq R^2 < 0.50$	Weak

Source: Subhaktiyasa (2024), Zeng et al. (2021)

3.7.2.9 Effect Size (f^2)

f^2 assesses how the independent variable actively contributes to explain the dependent variable regarding R^2 (Zeng et al., 2021). It also explains the presence of partial or full mediation (Purwanto & Sudargini, 2021).

Table 3.7: *f^2 Table*

Values	Effect Size
$f^2 \geq 0.35$	Large
$0.15 \leq f^2 < 0.35$	Medium
$0.02 \leq f^2 < 0.15$	Small

Source: Purwanto & Sudargini (2021), Subhaktiyasa (2024)

3.7.2.10 Predictive Relevance (Q^2)

Q^2 evaluates the model's accuracy in predicting the latent structure (Akbari et al., 2023). Generally, a Q^2 value of more than 0 indicates satisfactory predictive power of the structure model (Sobaih & Elshaer, 2022). Nevertheless, the widely used threshold is listed below.

Table 3.8: *Q^2 Table*

Values	**Predictive Power**
$Q^2 \geq 0.35$	Sound
$0.15 \leq Q^2 < 0.35$	Moderate
$0.02 \leq Q^2 < 0.15$	Weak

Source: Subhaktiyasa (2024), Zeng et al. (2021)

3.8 Conclusion

This chapter provides an overview of the research methodology used for this study, including the exploratory quantitative research design, data collection techniques, sample strategies, construct measures, and data processing stages. PLS-SEM is used as the analysis technique to evaluate the measurement and structural models. Overall, these methodological choices ensure that this research is conducted in a systematic, valid, and reliable manner to provide a strong foundation for the results discussion in the following chapters.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Data collected for the study was analysed, showcasing the data results and explaining them. Descriptive analysis's goal is to characterise the respondents' demographic profile and other pertinent traits. Furthermore, the measurement model was assessed in order to determine the validity and reliability of the constructs. The structural model assessment was then carried out to look at the connections between the variables and test the assumptions that had been put forth. The analyses were all completed using SmartPLS 4.1.1.8.

4.1 Descriptive Analysis

Descriptive analysis was performed to understand and interpret data collected. Demographic details were collected from Section A of the questionnaire and analysed, whereas data collected on variables and mediator are in Section B and C.

4.1.1 Respondents' Demographic Profile

Four types of data were collected from respondents in this study, including gender, age group, place of residence, and education level.

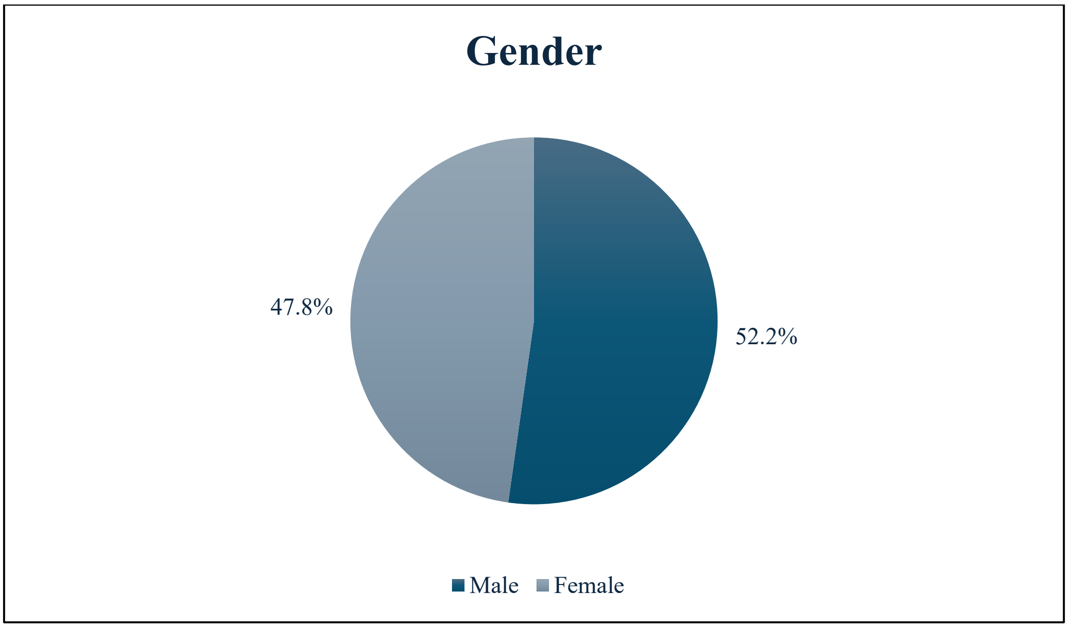
4.1.1.1 Gender

Table 4.1: *Descriptive Analysis for Gender*

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Male	233	52.2	233	52.24
Female	213	47.8	446	100

Source: Developed for Study

Figure 4.1: Descriptive Analysis for Gender



Source: Developed for Study

Table 4.1 and Figure 4.1 above indicate that 233 of the total 446 respondents (52.24%) are male. Conversely, 213 respondents are female, making up 47.76% of the total respondents.

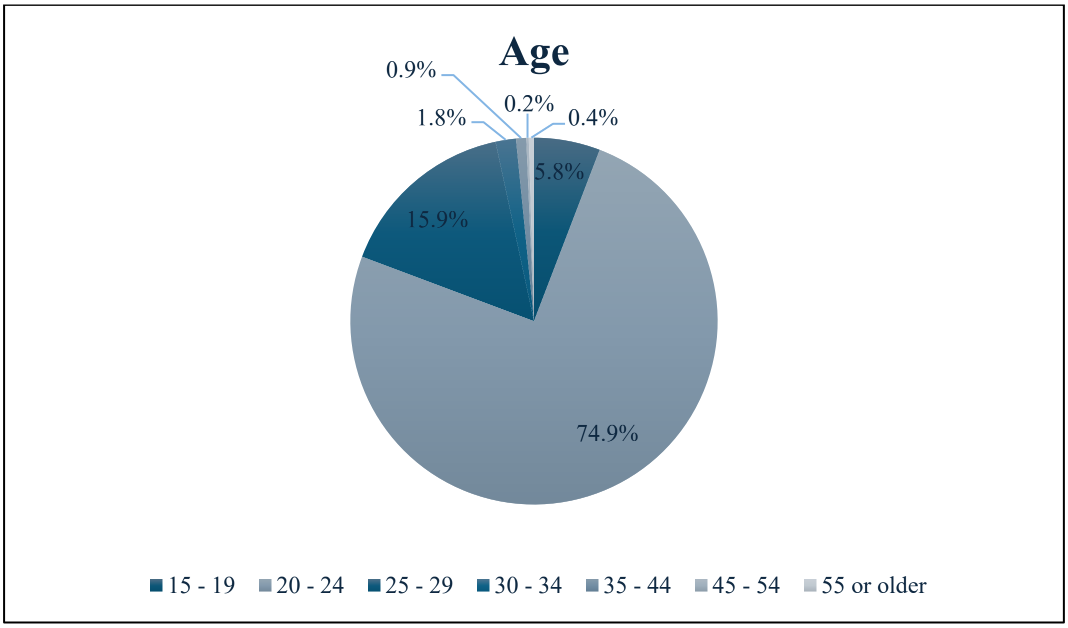
4.1.1.2 Age

Table 4.2: *Descriptive Analysis for Age*

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
15 - 19	26	5.8	26	5.8
20 - 24	334	74.9	360	80.7
25 - 29	71	16	431	96.7
30 - 34	8	1.8	439	98.5
35 - 44	4	0.9	443	99.4
45 - 54	1	0.2	444	99.6
55 or older	2	0.4	446	100

Source: Developed for Study

Figure 4.2: Descriptive Analysis for Age



Source: Developed for Study

Table 4.2 and Figure 4.2 show the frequency and percentage distribution of respondents by age. Out of the total of 446 respondents, 26 respondents (5.8%) are within the age 15 - 19 years; 334 respondents (74.9%) are within the age 20 - 24 years; and 71 respondents (16%) are within the age 25 - 29 years. These three categories of ages total up to 431 (96.7%), which represents the Gen Z population. However, 8 respondents (1.8%) are between the ages of 30 and 34; 4 respondents (0.9%) are between the ages of 35 and 44; 1 respondent (0.2%) is between the ages of 45 and 54; and 2 respondents (0.4%) are 55 years of age or older.

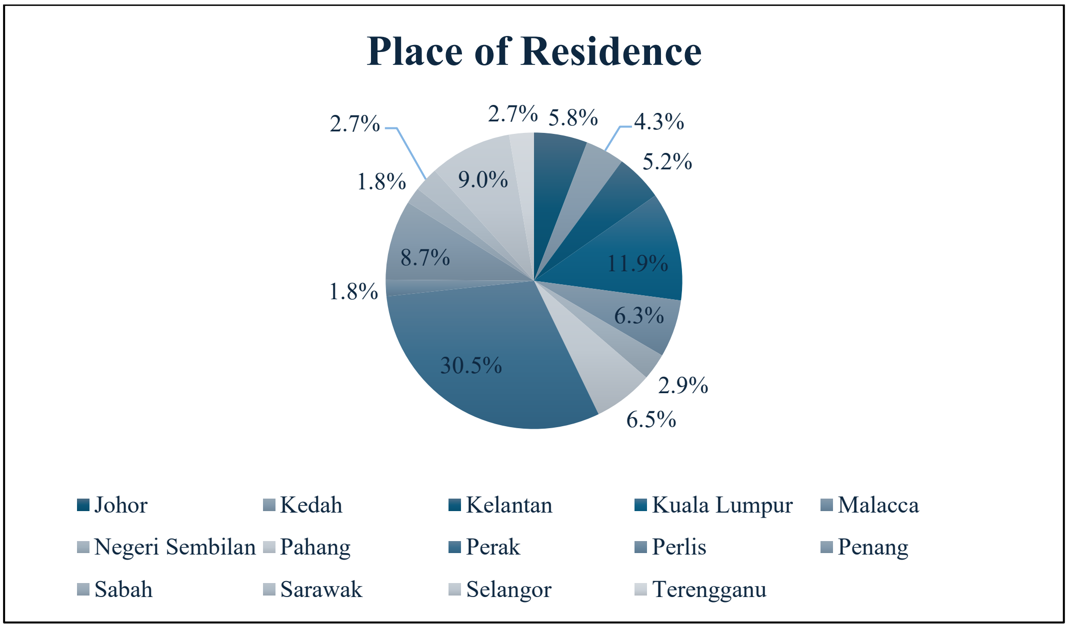
4.1.1.3 Place of Residence

Table 4.3: *Descriptive Analysis for Place of Residence*

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Johor	26	5.8	26	5.8
Kedah	19	4.3	45	10.1
Kelantan	23	5.2	68	15.3
Kuala Lumpur	53	11.9	121	27.2
Malacca	28	6.3	149	33.5
Negeri Sembilan	13	2.9	162	36.4
Pahang	29	6.5	191	42.9
Perak	136	30.5	327	73.4
Perlis	8	1.8	335	75.2
Penang	39	8.7	374	83.9
Sabah	8	1.8	382	85.7
Sarawak	12	2.7	394	88.4
Selangor	40	9	434	97.3
Terengganu	12	2.7	446	100

Source: Developed for Study

Figure 4.3: Descriptive Analysis for Place of Residence



Source: Developed for Study

Table 4.3 and Figure 4.3 show the frequency and percentage distribution of respondents' place of residence. According to the results, majority of the respondents are from Perak with 136 respondents (30.5%), followed by Kuala Lumpur with 53 respondents (11.9%), Selangor with 40 respondents (9.0%), and Penang with 39 respondents (8.7%). This shows that the results of this questionnaire represent a substantial proportion of the community living in a more urbanised or economically active region in Malaysia. Whereas states such as Pahang with 29 respondents (6.5%), Malacca with 28 respondents (6.3%), Johor with 26 respondents (5.8%), and Kelantan with 23 respondents (5.2%) contributed a moderate proportion to this questionnaire; while Kedah with 19 respondents (4.3%), Negeri Sembilan with 13 respondents (2.9%), Sarawak with 12 respondents (2.7%), Terengganu with 12 respondents (2.7%), Perlis with 8 respondents (1.8%), and Sabah with 8 respondents (1.8%), recorded lower percentages, each below 5%. Overall, the sample reflects a geographically diverse distribution.

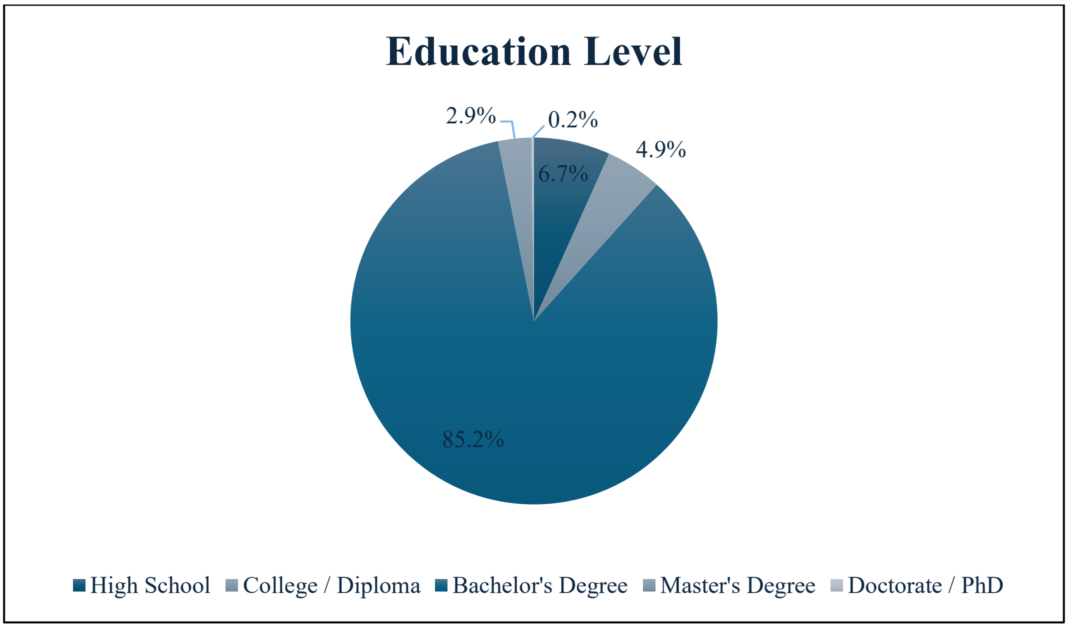
4.1.1.4 Education Level

Table 4.4: *Descriptive Analysis for Education Level*

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
High School	30	6.7	30	6.7
College / Diploma	22	4.9	52	11.6
Bachelor's Degree	380	85.2	432	96.8
Master's Degree	13	2.9	445	99.7
Doctorate / PhD	1	0.2	446	100

Source: Developed for Study

Figure 4.4: Descriptive Analysis for Education Level



Source: Developed for Study

The frequency and percentage distribution of respondents' educational levels are shown in Table 4.4 and Figure 4.4. The diagram presents that most of them hold a Bachelor's degree with 380 respondents (85.2%), followed by a smaller proportion with High School education with 30 respondents (6.7%) and College / Diploma qualifications with 22 respondents (4.9%). Only a few respondents possess postgraduate qualifications, with Master's degree holders accounting for 2.9% (13 respondents) and Doctorate / PhD holders at 0.2% (1 respondent).

4.1.2 Central Tendencies and Dispersion Measurement of Construct

Questions regarding the independent, dependent, and mediating variables in the questionnaire were evaluated in this section. The evaluation includes the mean value, standard deviation (SD) value, and skewness value of each variable independently.

4.1.2.1 Performance Expectancy of Digital investment Platforms (PE)

The questions modified for this study's questionnaire are displayed in Table 4.5 below, along with the corresponding mean, mean ranking, SD, SD ranking, and skewness. PE1 represents the first question on performance expectancy of digital investment platforms in the questionnaire, and it follows.

Table 4.5: *PE*

	Statement	Mean	SD	Skewness	Mean Ranking	SD Ranking
PE1	Using digital investment platform would help me accomplish	3.791	0.958	-0.508	1	4

	financial goals more quickly.					
PE2	I intend to keep using digital investment platform for making sustainable investment decisions.	3.747	0.998	-0.534	4	3
PE3	I believe that using digital investment platform would increase my productivity.	3.76	1.017	-0.712	2	1
PE4	I intend to use digital investment platform in the near future due to its performance.	3.758	1.013	-0.656	3	2

**Note: PE – Performance Expectancy

Source: Developed for Study

The dependent variable was examined. According to Table 4.5, the mean and standard deviation of the constructs are PE1 (3.791, 0.958), PE2 (3.747, 0.998), PE3 (3.76, 1.017), PE4 (3.758, 1.013) respectively. Overall, the mean value for PE which ranges from 3.747 to 3.791 indicates that respondents are more inclined towards "Agree". Besides, the standard deviation values range from 0.958 to 1.017 shows that there is a moderate level of variability and the respondents' responses are relatively consistent. The skewness value for PE ranges from -0.508 to -0.712, which shows a moderately skewed data distribution and that the responses are slightly concentrated toward higher values.

4.1.2.2 Social Influence (SI)

The questions modified for this study's questionnaire are displayed in Table 4.6 below, along with the corresponding mean, mean ranking, SD, SD ranking, and skewness. SI1 represent the first question on social influence towards the performance expectancy of digital investment platforms (PE) in the questionnaire, and it follows.

Table 4.6: *SI*

	Statement	Mean	SD	Skewness	Mean Ranking	SD Ranking
SI1	People who are important and who can influence my behaviour think that I should use digital investment platform.	3.652	0.995	-0.563	1	4
SI2	Financial experts and mentors I follow encourage the use of digital investment platforms.	3.603	0.999	-0.483	3	3
SI3	My peers believe that digital investment platforms are beneficial for	3.621	1.006	-0.527	2	2

	making financial decisions.					
SI4	Most people in my social circle (e.g., friends, colleagues) use digital investment platforms to support their investment.	3.572	1.03	-0.453	4	1

**Note: SI – Social Influence

Source: Developed for Study

For the first independent variable, social influence, according to Table 4.6, the mean and standard deviation of the constructs are SI1 (3.652, 0.995), SI2 (3.603, 0.999), SI3 (3.621, 1.006), SI4 (3.572, 1.03) respectively. Overall, the mean value for SI which ranges from 3.572 to 3.652 indicates that respondents are more inclined towards “Agree”. Besides, the standard deviation values range from 0.995 to 1.03 shows that there is a moderate level of variability and the respondents’ responses are relatively consistent. The skewness value for SI ranges from -0.453 to -0.563, which shows a normally skewed data distribution while the responses are slightly concentrated toward higher values.

4.1.2.3 Perceived Usefulness (PU)

The questions modified for this study’s questionnaire are displayed in Table 4.7 below, along with the corresponding mean, mean ranking, SD, SD ranking, and skewness. PU1 represent the first question on perceived usefulness towards the performance expectancy of digital investment platforms (PE) in the questionnaire, and it follows.

Table 4.7: *PU*

	Statement	Mean	SD	Skewness	Mean Ranking	SD Ranking
PU1	The digital investment platform can improve the overall performance of my sustainable investment portfolio.	3.774	0.952	-0.535	1	4
PU2	I believe that the digital investment platform provides useful insights into sustainable investment opportunities.	3.715	1.04	-0.584	3	1
PU3	The digital investment platform is useful in aligning my investment strategy with sustainability.	3.7	1.013	-0.488	4	3
PU4	Using digital investment platform would improve my	3.722	1.026	-0.585	2	2

	investment performance and productivity.					

**Note: PU – Perceived Usefulness

Source: Developed for Study

For perceived usefulness, according to Table 4.7, the mean and standard deviation of the constructs are PU1 (3.774, 0.952), PU2 (3.715, 1.04), PU3 (3.7, 1.013), PU4 (3.722, 1.026) respectively. Overall, the mean value for PU which ranges from 3.7 to 3.774 indicates that respondents are more inclined towards "Agree". Besides, the standard deviation values range from 0.952 to 1.04 shows that there is a moderate level of variability and the respondents' responses are relatively consistent. The skewness value for PU ranges from -0.488 to -0.585, which shows a normally skewed data distribution while the responses are slightly concentrated toward higher values.

4.1.2.4 Perceived Ease of Use (PEOU)

The questions modified for this study's questionnaire are displayed in Table 4.8 below, along with the corresponding mean, mean ranking, SD, SD ranking, and skewness. PEOU1 represent the first question on perceived ease of use towards the performance expectancy of digital investment platforms (PE) in the questionnaire, and it follows.

Table 4.8: *PEOU*

	Statement	Mean	SD	Skewness	Mean Ranking	SD Ranking
PEOU1	I would find it easy to get digital investment	3.72	0.991	-0.566	1	2

	platform to do what I want it to do.					
PEOU2	I would find digital investment platform to be flexible to interact with.	3.67	0.989	-0.514	3	3
PEOU3	It would be easy for me to become skilful at using digital investment platform.	3.655	1.023	-0.593	4	1
PEOU4	I would find digital investment platform easy to use.	3.711	0.979	-0.515	2	4

**Note: PEOU – Perceived Ease of Use

Source: Developed for Study

For perceived ease of use, according to Table 4.8, the mean and standard deviation of the constructs are PEOU1 (3.72, 0.991), PEOU2 (3.67, 0.989), PEOU3 (3.655, 1.023), PEOU4 (3.711, 0.979) respectively. Overall, the mean value for PEOU which ranges from 3.655 to 3.72 indicates that respondents are more inclined towards “Agree”. Besides, the standard deviation values range from 0.979 to 1.023 shows that there is a moderate level of variability and the respondents’ responses are relatively consistent. The skewness value for PEOU ranges from -0.514 to -0.593, which shows a normally skewed data distribution while the responses are slightly concentrated toward higher values.

4.1.2.5 Hedonic Motivation (HM)

The questions modified for this study's questionnaire are displayed in Table 4.9 below, along with the corresponding mean, mean ranking, SD, SD ranking, and skewness. HM1 represent the first question on hedonic motivation towards the performance expectancy of digital investment platforms (PE) in the questionnaire, and it follows.

Table 4.9: *HM*

	Statement	Mean	SD	Skewness	Mean Ranking	SD Ranking
HM1	Using digital investment platform is fun.	3.751	0.972	-0.572	1	4
HM2	Using digital investment platform is enjoyable.	3.706	1.01	-0.619	2	3
HM3	I enjoy using digital investment platforms because they make my investment experience more fun and engaging.	3.601	1.081	-0.567	4	1
HM4	I find it exciting to interact with	3.621	1.06	-0.581	3	2

	digital investment platforms as it adds an element of novelty to my investing experience.					

**Note: HM– Hedonic Motivation

Source: Developed for Study

For hedonic motivation, according to Table 4.9, the mean and standard deviation of the constructs are HM1 (3.751, 0.972), HM2 (3.706, 1.01), HM3 (3.601, 1.081), HM4 (3.621, 1.06) respectively. Overall, the mean value for HM which ranges from 3.601 to 3.751 indicates that respondents are more inclined towards "Agree". Besides, the standard deviation values range from 0.972 to 1.081 shows that there is a moderate level of variability and the respondents' responses are relatively consistent. The skewness value for HM ranges from -0.567 to -0.572, which shows a normally skewed data distribution while the responses are slightly concentrated toward higher values.

4.1.2.6 Artificial Intelligence (AI)

The questions modified for this study's questionnaire are displayed in Table 4.10 below, along with the corresponding mean, mean ranking, SD, SD ranking, and skewness. AI1 represents the first question on artificial intelligence towards the performance expectancy of digital investment platforms (PE) in the questionnaire, and it follows.

Table 4.10: *AI*

	Statement	Mean	SD	Skewness	Mean Ranking	SD Ranking

AI1	My general knowledge about AI is more than sufficient compared to many.	3.702	0.997	-0.423	3	3
AI2	Learning and implementing innovations in AI applications are a priority for me.	3.749	0.993	-0.569	1	4
AI3	I take pleasure in using artificial intelligence applications.	3.695	1.038	-0.631	4	1
AI4	Learning artificial intelligence applications is an easy task for me.	3.72	1.02	-0.638	2	2

**Note: AI – Artificial Intelligence

Source: Developed for Study

The mediator was investigated. According to Table 4.10, the mean and standard deviation of the constructs are AI1 (3.702, 0.997), AI2 (3.749, 0.993), AI3 (3.695, 1.038), AI4 (3.72, 1.02) respectively. Overall, the mean value for AI which ranges from 3.695 to 3.749 indicates that respondents are more inclined towards "Agree". Besides, the standard deviation values range from 0.993 to 1.038 shows that there is a moderate level of variability and the respondents' responses are relatively consistent. The skewness value for SI ranges from -0.423 to -0.638, which shows a moderately skewed data distribution while the responses are slightly concentrated toward higher values.

4.2 Measurement Model Assessment

The measuring model assessment evaluated the validity and reliability of the constructs used in this investigation. Several criteria, including indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, are used in this study to assess the measurement model.

4.2.1 Indicator Reliability

Table 4.11: *Reliability and Validity Analysis*

Construct	Item	Outer Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Dependent Variable: Performance Expectancy of Digital Investment Platform	PE1	0.737	0.672	0.803	0.505
	PE2	0.725			
	PE3	0.707			
	PE4	0.671			
Independent Variable 1: Social Influence	SI1	0.624	0.683	0.807	0.513
	SI2	0.763			
	SI3	0.732			
	SI4	0.737			
Independent Variable 2: Perceived Usefulness	PU1	0.765	0.733	0.833	0.555
	PU2	0.758			
	PU3	0.712			
	PU4	0.745			
	PEOU1	0.725	0.714	0.823	0.538

Independent Variable 3: Perceived Ease of Use	PEOU2	0.75			
	PEOU3	0.728			
	PEOU4	0.73			
Independent Variable 4: Hedonic Motivation	HM1	0.665	0.771	0.853	0.594
	HM2	0.786			
	HM3	0.828			
	HM4	0.794			
Mediating Variable: Artificial Intelligence	AI1	0.71	0.683	0.808	0.512
	AI2	0.767			
	AI3	0.682			
	AI4	0.702			

Source: Developed for Study

The degree to which each indicator accurately measures the related latent construct is evaluated by indicator reliability. Outer loading refers to the regression coefficient between the indicators and the latent constructs. Outer loading values must meet a minimum threshold of 0.708 to be statistically significant (Fauzi, 2022; Subhaktiyasa, 2024). According to Table 4.11, the outer loading values for most indicators ranged from 0.624 to 0.828 which meets the recommended threshold of 0.708. However, several indicators such as PE4, SI1, HM1, AI3 have relatively low outer loadings of 0.671, 0.624, 0.665, and 0.682 respectively. However, all are still greater than 0.6, therefore all variables will be applied in statistical model to conduct prediction as the results are reliable and enforceable.

In order to measure the internal consistency of the constructs, composite reliability was evaluated in addition to outer loadings. If a construct's composite reliability value is higher than 0.70, it is considered to have good reliability (Bakhtiar et al., 2021; Cheung et al., 2024; Haji-Othman & Yusuff, 2022). According to Table 4.11, the composite reliability ranged from 0.803 to 0.853 which exceeded the recommended threshold of 0.70. This suggests that the measurement model has enough internal reliability and that the indicators consistently measure the corresponding constructs. Generally, HM demonstrates the strongest internal consistency with a reliability coefficient of 0.833.

4.2.2 Internal Consistency Reliability

Table 4.12: *Reliability Analysis - Cronbach's Alpha*

Type	Construct	Cronbach's Alpha	Reliability Test
Dependent Variable	Performance Expectancy of Digital Investment Platform (PE)	0.672	Questionable
Independent Variable	Social Influence (SI)	0.683	Questionable
	Perceived Usefulness (PU)	0.733	Acceptable
	Perceived Ease of Use (PEOU)	0.714	Acceptable
	Hedonic Motivation (HM)	0.771	Acceptable
Mediating Variable	Artificial Intelligence (AI)	0.683	Questionable

Source: Developed for Study

Cronbach's Alpha assesses how well indicators within a construct correlate with one another and shows how reliable the measuring scale is. Technically, a Cronbach alpha coefficient of 0.70 and above is an indicator for good internal consistency (Damianova et al., 2024; Kennedy, 2022). According to Table 4.12, the Cronbach's Alpha values ranged from 0.672 to 0.771. While most constructs such as PU (0.733), PEOU (0.714) and HM (0.771) exceeded the suggested threshold of 0.70 which explains good internal consistency, several constructs such as PE (0.672), SI (0.683) and AI (0.683) have Cronbach's Alpha value slightly below the recommended threshold of 0.70. Nevertheless, these values are acceptable for exploratory research and early-stage model development.

4.2.3 Convergent Validity

The degree to which a construct's indicators have a significant amount of variance in common is known as convergent validity. According to Shrestha (2021), convergent validity is confirmed when the Average Variance Extracted (AVE) is greater than or equal to 0.50. According to Table 4.11, the AVE values ranged from 0.505 to 0.594. AVE values above the suggested threshold of 0.50 were obtained by all constructs, indicating satisfactory convergent validity. Specifically, HM has an AVE value of 0.594, followed by PU (0.555), PEOU (0.538), SI (0.513), AI (0.512) and PE (0.505). Overall, the findings imply that the measurement model has respectable convergent validity and that the study's constructs are suitable for additional structural model research.

4.2.4 Discriminant Validity

Table 4.13: *HTMT Output*

	AI	**HM**	**PE**	**PEOU**	**PU**	**SI**
AI						
HM	0.757					
PE	0.976	0.833				
PEOU	0.828	0.757	0.875			
PU	0.892	0.689	1.012	0.779		
SI	0.753	0.8	0.919	0.725	0.818	

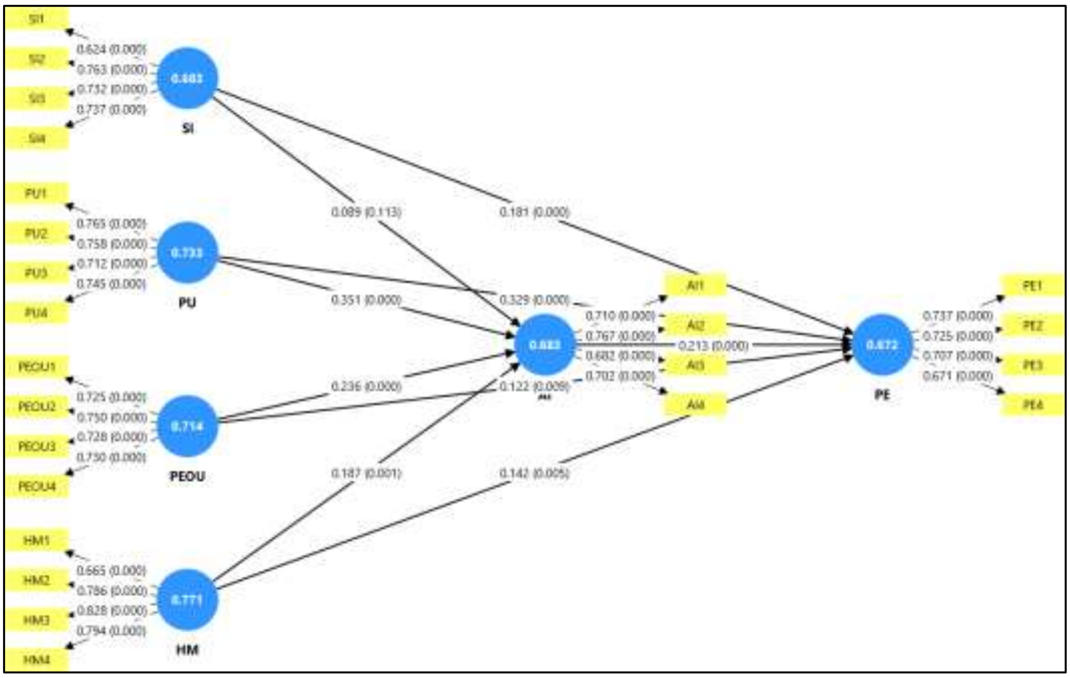
Source: Developed for Study

The ratio of correlations between constructs is examined by the Heterotrait-Monotrait Ratio (HTMT) criteria. Every construct should have an HTMT ratio of less than 0.90 or 0.85 if the constructions are conceptually more distinct (Cheung et al., 2023; Gelibolu & Mouloudj, 2025). According to Table 4.13, the HTMT values ranged from 0.725 to 1.012. While most of the constructs are below the recommended threshold of 0.90, the HTMT values between PE and AI (0.976), PE and PU (1.012), PE and SI (0.919) slightly exceeded the recommended threshold. This might be due to the conceptual similarity between the constructs and the related nature of their indicators. Nevertheless, the constructs were retained as they represent theoretically distinct concepts supported by prior literature.

4.3 Structural Model Assessment

This research employed Partial Least Squares Structural Equation Modeling (PLS-SEM) following Magno et al. (2024)'s guidelines for method. In order to produce a reliable estimate, bootstrapping with 10,000 subsamples was used to assess the direct and indirect path coefficients. Statistical significance was tested on a two-tailed test with $\alpha = 0.05$. Structural model outputs are illustrated in Figure 4.5.

Figure 4.5: Structural Model Assessment



Sources: Developed for Study

The structural model is used to evaluate the relationship between the independent variables, SI, PU, PEOU, HM, with the dependent variable PE. According to Figure X, most of the outer loadings of the measurement model exceed the recommended threshold of 0.70 thus demonstrating the validity and reliability of the constructs employed in this research.

The construct SI is measured using 4 indicators, namely SI1, SI2, SI3, and SI4, with outer loading values of 0.624, 0.763, 0.732, and 0.737 respectively. Although one of the indicators recorded an outer loading value slightly below the threshold of 0.70, the value remains within the acceptable range suggested in Shwedeh et al. (2024). These metrics show how much a person's decision to use digital investment platforms is influenced by their social circle, including family, friends, and influential individuals. The satisfactory outer loading values indicate that respondents consider social opinions and recommendations when determining the performance expectancy of digital investment platforms.

The construct PU is operationalized using four indicators, namely PU1, PU2, PU3, and PU4, with outer loading values of 0.765, 0.758, 0.712, and 0.745, all above the recommended threshold of 0.70. These indicators measure the degree to which respondents believe that using a digital investment platform enhances their investment performance. The strong outer loading values explains that the indicators effectively capture perceptions related to improved efficiency, better investment decision-making, and enhanced financial outcomes when using digital investment platforms.

The construct PEOU is measured using four indicators, namely PEOU1, PEOU2, PEOU3, and PEOU4, with outer loading values of 0.725, 0.750, 0.728, 0.730. All indicators exceed the threshold of 0.70, which captures the respondents' perceptions regarding the usability and simplicity of digital investment platforms, such as how easy the platforms are to be learned, navigated and operated. The high outer loading values indicate that respondents consistently evaluate the user-friendliness of the platform when forming their perceptions.

The construct HM is measured by four indicators, namely HM1, HM2, HM3, and HM4, with outer loading values of 0.665, 0.786, 0.828, and 0.794 respectively. Similarly, one indicator recorded an outer loading value slightly below the recommended threshold of 0.70, however, it remains acceptable to the recommended guidelines by Shwedeh et al. (2024) when the overall construct reliability is satisfactory. These satisfactory indicators show that respondents found using digital investing platforms to be entertaining and interesting, which increased their motivation to use them overall.

Furthermore, the structural model results indicate that the independent constructs PU, PEOU, and HM have direct relationships with AI, with path coefficients of 0.351, 0.236, and 0.187. This suggests that these factors contribute to shaping users' perceptions and acceptance of artificial intelligence features within digital investment platforms. However, SI was found to be insignificant, with a path coefficient of 0.089, indicating that SI does not significantly affect users' perceptions or adoption of AI within digital investment platforms. This suggests that respondents may rely more on their personal evaluation of the digital platform's functionality and benefits rather than the opinions from others when considering the use of AI features in digital investment platforms.

In addition, AI demonstrates a significant relationship with PE with a path coefficient of 0.213. The construct PE is measured using four indicators, namely PE1, PE2, PE3, and PE4, with outer loading values of 0.737, 0.725, 0.707, and 0.671 respectively, including one indicator slightly below the recommended threshold of 0.70, which remains acceptable based on established guidelines. These indicators reflect respondents' expectations regarding the extent to which digital investment platforms enhance the investment performance and experience of users, improve efficiency, and support better financial decision-making.

Overall, the structural model's findings verify that PU, PEOU, and HM influence how AI is viewed and adopted, which raises the PE of digital investment platforms. However, SI acts the opposite. The acceptable outer loading values further support the reliability of the constructs, while the structural relationships provide empirical evidence for the proposed research framework.

4.3.1 Collinearity

Table 4.14: *Outputs of Variance Inflation Factors*

	AI	HM	PE	PEOU	PU	SI
AI			2.046			
HM	1.818		1.889			
PE						

PEOU	1.762	1.876
PU	1.808	2.06
SI	1.843	1.859

Sources: Developed for Study

Description. Table 4.14 indicates that the VIF values for SI, PU, PEOU, and HM ranged from 1.762 to 2.06, all of which are below the suggested range of below 5.0. These results suggest that multicollinearity is not present among the predictor constructs in the model.

4.3.2 Assess Path Coefficients

Table 4.15: *Path Coefficient, Standard Error, T-Value, P-Value and Hypotheses Testing*

Hypothesis	Description	Beta Value (ß)	Standard Error	T-Value	P-Value	Decision
H_1	SI → PE	0.181	0.045	4.026	0.000	Do not reject H_1
H_2	PU → PE	0.329	0.053	6.244	0.000	Do not reject H_2
H_3	PEOU → PE	0.122	0.048	2.55	0.011	Do not reject H_3
H_4	HM → PE	0.142	0.05	2.838	0.005	Do not reject H_4
H_5	SI → AI	0.089	0.056	1.597	0.110	Reject H_5
H_6	PU → AI	0.351	0.058	6.008	0.000	Do not reject H_6

H_7	PEOU → AI	0.236	0.062	3.822	0.000	Do not reject H_7
H_8	HM → AI	0.187	0.057	3.281	0.001	Do not reject H_8
H_9	AI → PE	0.213	0.051	4.179	0.000	Do not reject H_9

Source: Developed for Study

According to the research study's structural equation modeling results, the hypothesised relationships were investigated at a significance level of 0.05 using the corresponding path coefficients, standard errors, t-values, and p-values. The findings provide empirical evidence regarding the relationships between SI, PU, PEOU, HM, AI and PE.

The first hypothesis (H_1) examined the relationship between SI and PE. The results show a path coefficient of 0.181, a t-value of 4.026, and a p-value of 0.000. Since the p-value is 0.000, the relationship between SI and PE is positive. This suggests that the influence of peers or family members positively affects users' expectations regarding the performance expectancy of digital investment platforms. Therefore, H_1 is not rejected.

The second hypothesis (H_2) tested the relationship between PU and PE. The results show a path coefficient of 0.329, a t-value of 6.244, and a p-value of 0.000. Since the p-value is 0.000, the relationship between PU and PE is positive. This suggests that users who perceive digital investment platforms as beneficial and effective in improving their investment performance tend to have higher expectations regarding the platform's performance. Therefore, H_2 is not rejected.

The third hypothesis (H_3) investigated the relationship between PEOU and PE. The results show a path coefficient of 0.122, a t-value of 2.55, and a p-value of 0.011, indicating a positive relationship between the two constructs. This suggests that when digital investment platforms are perceived as easy to use and user-friendly, users are more likely to expect better performance from the digital investment platform. Therefore, H_3 is not rejected.

The fourth hypothesis (H_4) investigated the relationship between HM and PE. The results show a path coefficient of 0.142, a t-value of 2.838, and a p-value of 0.005. This indicates that HM has a positive effect on PE. This suggests that the enjoyment or pleasure experienced by users when using digital investment platforms contributes to users' expectations regarding the digital platform's performance. Thus, H_4 is not rejected.

The fifth hypothesis (H_5) assessed the mediating role of AI in the relationship between SI and PE. The results show a path coefficient of 0.089, a t-value of 1.597, and a p-value of 0.110. This suggest that AI does not mediate the relationship between SI and PE. Therefore, H_5 is rejected.

The sixth hypothesis (H_6) examined whether AI mediates the relationship between PU and PE. The result shows a path coefficient of 0.351, a t-value of 6.008, and a p-value of 0.000. This indicates that AI mediates the relationship between PU and PE. Consequently, H_6 is not rejected.

The seventh hypothesis (H_7) investigated whether AI mediates the relationship between PEOU and PE. The results show a path coefficient of 0.236, a t-value of 3.822, and a p-value of 0.000, suggesting that AI mediates the relationship between PEOU and PE. Consequently, H_7 is not rejected.

The eighth hypothesis (H_8) examined the mediating role of AI between HM and PE. The results show a path coefficient of 0.187, a t-value of 3.281, and a p-value of

0.000. These results indicate that AI mediates the relationship between HM and PE. Consequently, H_8 is not rejected.

The ninth hypothesis (H_9) investigated the relationship between AI and PE. The results show a path coefficient of 0.213, a t-value of 4.179, and a p-value of 0.000. Since the p-value is 0.000, the relationship between AI and PE is positive. This suggests that the presence of AI features in digital investment platforms enhances users' expectations regarding the platform's performance. Therefore, H_9 is not rejected.

4.3.3 Coefficient of Determination (R^2)

Table 4.16: *Determination of co-efficient (R^2)*

	R-square	**R-square adjusted**
AI	0.511	0.507
PE	0.649	0.645

Sources: Developed for Study

R^2 determines how much of the variance in the dependent variable can be explained by the independent variables. Higher R^2 values suggest a better fit of the model (Williams et al., 2024). According to Table 4.16, the R^2 value for AI is 0.511, which reflects that SI, PU, PEOU, and HM collectively explain 51.1% of the variance in AI. This suggests that the construct has a moderate level of explanatory power.

Furthermore, the R^2 value for PE is 0.649, which reflects that AI and the independent variables (SI, PU, PEOU, HM) explain 64.9% of the variance in PE. This suggests that when it comes to forecasting the performance expectancy of digital investing platforms, the model has a modest explanatory ability.

Overall, the R^2 values indicate that the structural model explains the relationships between the constructs in this research study with a reasonable degree of predictive accuracy.

4.3.4 Effect Size (f^2)

Table 4.17: *Determination of Effect Size (f^2)*

	AI	HM	PE	PEOU	PU	SI
AI			0.063			
HM	0.039		0.03			
PE						
PEOU	0.065		0.023			
PU	0.139		0.149			
SI	0.009		0.05			

Source: Developed for Study

f^2 assesses how the independent variable actively contributes to explain the dependent variable regarding R^2 (Zeng et al., 2021). Large effect sizes are defined as f^2 greater than or equal to 0.35; medium effect sizes are defined as f^2 between 0.15 and 0.35; and small effect sizes are defined as f^2 between 0.02 and 0.15. According to Table 4.17, the f^2 of all constructs have a small effect size on both AI and PE. This suggests that although the construct contributes to explaining the variance of PE, its impact is relatively limited as compared to other constructs in the model.

4.3.5 Predictive Relevance (Q^2)

Table 4.18: *Determination of Predictive Relevance (Q^2)*

	Q^2 predict
AI	0.494
PE	0.615

Source: Developed for Study

Q^2 evaluates the model's accuracy in predicting the latent structure (Akbari et al., 2023). Higher Q^2 values imply stronger predictive capability, whereas a Q^2 value higher than zero indicates that the dependent variable can be predicted by the model. The blindfolding operation results show that the Q^2 value for AI is 0.494 and the Q^2 value for PE is 0.615, as shown in Table 4.18. The findings imply that the structural model exhibits strong predictive relevance for PE since both values are higher than 0.35.

4.3.6 Mediation Analysis

Mediation analysis was conducted to examine the role of AI as a mediating variable in the relationships between SI, PU, PEOU, HM, and dependent variable PE. In Structural Equation Modeling, mediation is assessed by evaluating the significance of the indirect effects using the bootstrapping procedure.

Table 4.19: *Mediation Analysis*

Hypothesis	Description	Original sample	Indirect Effect	T-value	P-value	Significance of Correlation ($p < 0.05$)	Decision

H_5	SI → AI → PE	0.019	0.013	1.421	0.155	0.155	Reject H_5
H_6	PU → AI → PE	0.075	0.023	3.259	0.001	0.001	Do not reject H_6
H_7	PEOU → AI → PE	0.05	0.017	2.992	0.003	0.003	Do not reject H_7
H_8	HM → AI → PE	0.04	0.016	2.505	0.012	0.012	Do not reject H_8

Source: Developed for Study

Table 4.19 indicates that the indirect effect of SI on PE through AI is not significant as the p-value (0.155) exceeds the significance level of 0.05. The result suggests that AI does not mediate the relationship between SI and PE. Therefore, H_5 is rejected. This finding implies that users may rely more on individual perceptions rather than external opinions such as AI robo-advisory when evaluating the performance of digital investment platforms.

In contrast, the indirect effect of PU on PE through AI is significant as the p-value (0.001) is lower than the significance level of 0.05, indicating that AI mediates between PU and PE. Therefore, do not reject H_6. This implies that consumers who think digital investment platforms are helpful are more inclined to appreciate AI features, which raises their expectations for the performance of the platforms.

Similarly, the indirect effect of PEOU on PE through AI is also significant with a p-value of 0.003 more than the level of significance of 0.05, therefore, do not reject H_7. This implies that user-friendly platforms encourage the adoption of AI features, which subsequently improve the performance expectancy of digital investment platforms.

Furthermore, the indirect effect of HM on PE through AI is significant as well, with a p-value of 0.012, more than the level of significance of 0.05, suggesting that AI mediates this relationship. Therefore, do not reject H_8. According to this research, users' enjoyment of digital investment platforms might increase their involvement with AI features, which in turn raises their expectations for the platforms' success.

Overall, the mediation analysis demonstrates that AI plays an important role in mediating the relationships between PU, PEOU and HM with PE, while there is no mediating effect found between SI and PE. There findings highlight the importance of AI as a mechanism through which user perceptions and experiences influence their expectations towards digital investment platforms.

4.4 Conclusion

The data analysis and conclusions, including the evaluation of the measurement and structural models, were provided in this chapter. The results confirmed that the constructs achieved acceptable levels of reliability and validity. The structural model findings indicated that PU, PEOU and HM significantly influence PE, while SI was found to be insignificant. Additionally, AI was found to mediate most of the relationships, highlighting its important role in shaping user's performance expectations towards digital investment platforms.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

The details in results that were revealed in Chapter 4 will be further explained in Chapter 5. The factors that have guided these findings to give a better insight into the relationships identified will be analysed. Furthermore, limitations of this study and some areas which could have influenced the findings are also explained. Recommendations on future research are also provided to follow in further undertakings. Lastly, this study is completed with the conclusion synthesising the rest of the findings to reach final conclusions.

5.1 Discussion of Major Findings

Table 5.1: *Bootstrapping Test Summary*

Hypothesis	Description of Variables	Beta Value (ß)	P-value	Decision
H_1	SI → PE	0.181	0.000	**Significant**
H_2	PU → PE	0.329	0.000	**Significant**
H_3	PEOU → PE	0.122	0.011	**Significant**
H_4	HM → PE	0.142	0.005	**Significant**
H_5	SI → AI → PE	0.089	0.110	**Not Significant**

H_6	PU → AI → PE	0.351	0.000	**Significant**
H_7	PEOU → AI → PE	0.236	0.000	**Significant**
H_8	HM → AI → PE	0.187	0.001	**Significant**
H_9	AI → PE	0.213	0.000	**Significant**

Source: Developed for Study

Table 5.1 shows the correlation between independent variables SI, PU, PEOU, HM towards dependent variables, PE, with and without the mediating effect of mediating variable, AI, and the correlation between AI and PE. Through all hypotheses, most relationships between dependent variables and independent variables are significant except for H_5, the relationship between SI and PE through mediating variable of AI is insignificant. It can also be observed that all the correlation between variables are positive; thus, it can be concluded that AI turns out to be an effective mediating variable in this study.

5.1.1 Social Influence (SI) and Performance Expectancy of Digital Investment Platforms (PE)

Table 5.1 shows ß with 0.181 and p-value with 0.000, which indicates that social influence (SI) has a significant positive effect on performance expectancy of digital investment platforms in Malaysia. This demonstrates how the social environment affects Gen Z investors' impressions of the efficacy of digital investment platforms. This result is consistent with the AIDUA model put forth by Gursoy et al. (2019), which highlighted the significance of social impact in influencing how people view AI-driven technologies. The result of this research also aligns with previous studies from Febrianti & Darma (2023), Gan et al (2021), Irimia-Diéguez et al. (2023), Kim & Fan (2025), Oktafian (2022), Prastiawan et al. (2021), Soeta et al. (2023), Trivedi et al. (2022), Vishnu et al. (2023), and Xie et al. (2021). Roy et al. (2020) and Wei et al. (2021) also found that social influence have significantly enhanced the performance expectancy and technology adoption of users. Previous research shown that people rely more on recommendations from friends, family, and social media when embracing new technology.

Furthermore, Gen Z's investing choices in Malaysia are significantly shaped by social impact. According to Joseph et al. (2025), social platforms is one of the main channels for sharing financial information and experiences. This show a sign of social proof, where individuals consider a technology more effective when it is widely adopted or endorsed by others. Furthermore, social influence helps Gen Z investors to reduce uncertainty in dealing with investment. By observing others successfully using digital investment platforms, Gen Z investors increase their confidence and developed a high expectation on performance of return. Therefore, social influence remains as a significant factor in shaping performance expectancy of digital investment platforms.

5.1.2 Perceived Usefulness (PU) and Performance Expectancy of Digital Investment Platforms (PE)

The table show that the ß value and p-value of perceived usefulness (PU) is 0.329 and 0.000. It has the strongest positive effect on performance expectancy of digital investment platforms in Malaysia among all variables. This suggests that Gen Z investors prioritise and concentrate on the practical advantages of digital investment platforms. This is also supported by the Technology Acceptance Model (TAM) proposed by Davis (1989), which mentioned perceived usefulness is a key determinant of the process of adopting technology. This is also consistent with the previous studies of Venkatesh and Davis (2000), and Seiler and Fanenbruck (2021), who discovered that people are more inclined to use technology if they think it can improve performance. Similarly, previous studies such as Jadil et al. (2021), Ling

(2024), Prastiawan et al (2021), and Siagan (2022) supported this positive relationship between PU and PE.

In this study, AI-driven features such as robo-advisors, predictive analysis, and automated portfolio management have significantly improved the usefulness of digital investment platforms. These tools increased the efficiency and accuracy on decision-making, which directly link to higher performance expectancy (Ray, 2023; Ahmad & Mokal, 2024). In addition, Gen Z investors tend to be performance-oriented and results-driven. When they perceive that a platform can improve the investment results, they develop a stronger expectation regarding to the performance. This finding shows that usefulness and functional value of platforms is one of the crucial factors which influences the user expectations on the performance.

5.1.3 Perceived Ease of Use (PEOU) and Performance Expectancy of Digital Investment Platforms (PE)

The table shows perceived ease of use (PEOU) has 0.122 and 0.011 of ß value and p-value. Additionally, although the effect size is marginally smaller than that of perceived usefulness, perceived simplicity of use has a considerable impact on performance expectancy of digital investment platforms in Malaysia. This indicate that user-friendly platforms contribute a higher expectation of performance. Furthermore, TAM theory mentioned that perceived ease of use has influenced user perceptions and contribute to the performance outcomes (Davis, 1989). Studies by Gefen and Straub (2000) and Arifa (2025) also prove that a system which is easy to use or adopt will lead to higher satisfaction of individuals and improved perceived effectiveness. The result of this research aligns with previous research by Wandhe (2024), Seiler and Fanebruck (2021), and Istiqomah and Alfansi (2024), who similarly described how consumers are more inclined to adopt new technology if they believe it is simple to use and have a favourable attitude toward it.

In this case, AI technologies can improve the ease of use of digital investment platforms by simplifying the complex financial processes or information. There are some features such as automated recommendations and intuitive interfaces that can minimise the effort required to use the platform. This may benefit the user, especially Gen Z investors who are lack of advanced financial knowledge. However, the relatively smaller effect size indicates that perceived ease of use is just viewed as a basic requirement rather than a key advantage. Since Gen Z users are digital natives, they will expect the platforms will be easy to use. Hence, although ease of use contributes to performance expectancy, it is less influential compared to perceived usefulness.

5.1.4 Hedonic Motivation (HM) and Performance Expectancy of Digital Investment Platforms (PE)

From Table 5.1, we can observe that hedonic motivation (HM)'s ß value and p-value is 0.142 and 0.005, which implies that it also improves the digital investing platforms' performance expectations. This suggests that enjoyment, satisfaction, and emotional experience from using digital investment platforms have significantly influence the user's expectation on the performance. This finding is aligned with the AIDUA model, which was stated in previous study, that highlights the importance of intrinsic motivation in technology adoption. It is also supported by Anggraeni et al. (2021), Fernando et al. (2021), Hartelina et al. (2021), Lee et al. (2022), Nikolopoulou et al. (2021), Ramachandran et al. (2024), Sudirjo et al. (2023), and Yang et al. (2023) who found that hedonic motivation can enhance the user engagement and behavioural intention in digital environment.

For Gen Z investors, hedonic motivations can be enhanced through features such as interactive features, gamification, and personalized experiences can improve the user satisfaction, which lead to them shifting to a new platform and continue using (Rahmantari et al., 2024). These elements can make the investment process more engaging and enjoyable, particularly for Gen Z investors. Unlike traditional investment methods, AI-driven platforms provide a more user-friendly experience. However, compared to perceived usefulness, the effect is moderate. This indicates that enjoyment is important but not the main factor of influencing performance expectancy of digital investment platforms. Nevertheless, Gen Z investors who are highly engaged with digital content and experiences will still impact by hedonic motivation. It contributes to user engagement and indirectly enhances performance expectancy by increasing usage frequency and familiarity with the platform.

5.1.5 Artificial Intelligence (AI) Mediate Social Influence (SI) and Performance Expectancy of Digital Investment Platforms (PE)

The finding shows that there is an insignificant effect of Artificial Intelligence (AI) mediates the relationship between social influence and performance expectancy is slightly weaker as its ß value is 0.089 and p-value is 0.110 which more than 0.05. This suggests that social influence affects performance expectancy both directly and indirectly through users' perceptions of AI. People are more inclined to build trust and accept the AI-driven features of digital investment platforms when friends or influencers influence them to use them.

However, the relatively weak mediation effect indicate that AI is not the main factor in affecting the relationship between social influence and performance expectancy. This may be due to Gen Z investors being digital natives, are already familiar with AI technologies, thus, social influence tends to have more direct impact compared to being mediated by AI. In addition, the concerns about data privacy, transparency, and algorithmic bias may limit the strength of mediating effect by AI. According to previous studies, individuals will still be cautious when come to fully relying on AI Urus et al. (2022b). Therefore, although AI plays a mediating role, this finding suggests that trust in AI is still in developing stage among Gen Z investors. In order to strengthen this relationship, the platforms developers should focus on improving the transparency, trustworthiness, and explainability in AI platforms.

5.1.6 Artificial Intelligence (AI) Mediate Perceived Usefulness (PU) and Performance Expectancy of Digital Investment Platforms (PE)

Table 5.1 reveals ß value of AI mediating the relationship between perceived usefulness and performance expectancy of digital investment platform is 0.351 and p-value is 0.000, which indicates that perceived usefulness and performance expectations of digital investment platforms are strongly and significantly mediated by AI. This result can be explained by the prior research of Fatouros et al. (2024) and Bi et al. (2024), which emphasised that AI could improve the process of decision-making accuracy, efficiency, and predictive capabilities. AI technologies also help individuals to evaluate large datasets, identify market trends, and generate customised investment recommendations to increase the functional value of digital investment platforms.

Furthermore, in this study, AI features in platforms such as robo-advisors and machine learning algorithms have enhanced the forecasting accuracy. These capabilities can increase the effectiveness of digital investment platforms as compared to traditional investment methods. Moreover, the finding aligns with Huang et al. (2024), who found that AI integration enhances the service quality and improves the user perceptions of usefulness in financial advisory services. If users perceive AI tools as valuable, they have higher tendency to expect better performance outcomes from the platform. The strong mediating effect of AI also suggests that AI function is a main component in affecting perceived usefulness on the performance expectancy of digital investment platforms. It transforms digital investment platforms from a simple tool into intelligent systems that delivers superior performance. Therefore, developers should prioritise AI innovation and functionality to enhance perceived usefulness, as it has the most significant impact on performance expectancy.

5.1.7 Artificial Intelligence (AI) Mediate Perceived Ease of Use (PEOU) and Performance Expectancy of Digital Investment Platforms (PE)

The finding shows that the ß value and p-value of AI mediating between the relationship of perceived ease of use and performance expectancy of digital investment platforms is 0.236 and 0.000. This suggests that AI can improve users' expectations of performance by improving the usability of digital investment platforms. This result is supported by previous studies of Ramesh et al. (2023) and Osman and Mohamad (2024) who mentioned that AI can simplify the complex tasks and enhance user interaction through automation and personalisation. Chatbots, automatic suggestions, and user-friendly interfaces are examples of features that might lessen the work needed to embrace the platforms.

In addition, AI acts as an important role in simplifying investment decisions, especially for Gen Z investors that may have limited financial knowledge and investment experiences. By providing clear insights, recommendations, and automated processes, AI can reduce the cognitive effort and improve user confidence simultaneously. Additionally, people are more likely to think that the platform can produce superior performance results because AI can reduce the complexity of the system.

Compared to the direct impact of perceived ease of use towards the performance expectancy of digital investment platforms, the mediating role of AI is stronger. This indicates that AI acts as a key mechanism through which ease of use influences performance expectancy. Hence, the finding emphasises the importance of AI features integration that can enhance the adaptability, such as automation and simple and user-friendly design which can improve the overall user experience and expectation on performance.

5.1.8 Artificial Intelligence (AI) Mediate Hedonic Motivation (HM) and Performance Expectancy of Digital Investment Platform (PE)

Table 5.1 shows the ß value and p-value of AI mediating the relationship between hedonic motivation and performance expectancy of digital investment platforms is 0.187 and 0.001. This implies that while using digital investing platforms, AI raises user satisfaction and enjoyment levels. This result is similar with the prior research such as Singh and Kumar (2025) that stated the AI-powered platform provide personalised and interactive user experiences. AI also can enhance the user enjoyment through customised investment recommendations, real-time feedback, and adaptive user interfaces.

Moreover, the AI-driven features also play a crucial role for Gen Z investors who are familiar with the dynamic digital technology. People are more inclined to utilise a platform frequently and discover its features when they love using it. In addition, AI can strengthen hedonic motivation through gamification and personalisation. For example, progress tracking, achievement systems, and interactive dashboards can make investing more easily. However, the impact of hedonic motivation still remains moderate compared to perceived usefulness. This implies that although enjoyment enhances performance expectancy, but practical benefits is still playing a more dominant role. In summary, AI not only enhances the functional capabilities of digital investment platforms but also enriches overall user experience of Gen Z investors.

5.1.9 Artificial Intelligence (AI) and Performance Expectancy of Digital Investment Platform (PE)

From Table 5.1, we can observe that Artificial Intelligence (AI)'s ß value and p-value is 0.213 and 0.000, which implies that AI has a significant positive relationship with the digital investing platforms' performance expectations. This indicates that the integration of AI features such as robo-advisory, predictive analysis, and automated portfolio management enhances users' perception towards the performance expectancy of digital investment platforms. This result is aligned with prior studies by Kamuangu (2024) which revealed that AI enhances efficiency and personalisation. As AI-driven features become more sophisticated, users may perceive such platforms as effective in their investment decisions.

Not only that, studies by Samara et al. (2024), Fonseca et al. (2024), and Alufaisan et al. (2021) also reflect similar results which shows that AI affects the performance of a platform positively. As AI enhances the performance of digital investment platforms, the expectations and perceptions of users towards an efficient platform is met, thus increasing the chances of adoption of the digital investment platform.

5.2 Implication of Study

This study provided significant insights that are incredibly relevant to stakeholders in the digital investment ecosystem, particularly among Gen Z users in Malaysia. The results of this study highlights the role of AI tools in shaping users' performance expectancy toward digital investments platforms. The results proved the significant relationships stated in the study except H_5, the mediating role of AI between social influence and performance expectancy. AI tools have a significant mediating effect between perceived usefulness, perceived ease of use, hedonic motivation and performance expectancy. This is expected to enhance decision-making efficiency, improve investment outcomes, and promote informed behaviour among Gen Z investors. Hence, this study suggests that investors should leverage AI-driven functionalities, such as robo-advisory services and personalized financial recommendations when engaging in digital investment platforms.

Moving on, the findings provided valuable implications for regulatory bodies. Since AI tools, perceived usefulness, perceived ease of use, social influence, and hedonic motivation are significant determinants of performance expectancy, the need to establish effective regulatory frameworks governing the use of AI in financial services is essential. Policymakers should prioritise issues related to data privacy and algorithmic transparency to ensure a safe and trustworthy digital investment environment, whereas authorities should also foster a balanced approach between digital innovation and regulatory oversight, so users are encouraged to adopt digital investment platforms while protecting users' interests and data privacy. This not only can ensure the users' trust in using such services but also foster growth of digital investment industry.

Furthermore, this study offers important implications for organisations in the financial technology and digital investment industry. AI tools are crucial to user engagement and perceived usefulness. The results demonstrated that while social influence has little effect on performance expectancy, perceived usefulness has the biggest impact. Thus, rather than social influence, organisations should prioritise investment in AI usability and system design.

Lastly, this study also provides directions for future research. Future studies may further explore why mediating role of AI between social influence and performance expectancy was not supported in this study, particularly in the context of Gen Z users. Subsequent research can also extend this model by integrating additional variables. This can better understand user behaviour in digital investment adoption. Therefore, this study, grounded in TAM and AIDUA, serves as a foundational framework that can be further expanded to contribute to the knowledge in fintech adoption and AI-driven financial decision-making.

5.3 Limitations of Study

Firstly, this study is based on existing research model and includes a limited number of variables. This study focuses on variables such as social influence (SI), perceived usefulness (PU), perceived ease of use (PEOU), hedonic motivation (HM), and AI tools as a mediator. However, this study remains within the scope of existing model, and other potentially relevant factors were not included. A more thorough understanding of user behaviour and technology adoption in digital investment contexts may be limited by the omission of other factors.

Secondly, the respondents are limited, primarily focusing on students aged 20 to 24 years, with a Bachelor's Degree qualification. This implies that the findings are mainly from certain respondents. This concentration restricts the findings' applicability to people with varied educational backgrounds, even while it enables a more focused explanation of users' behaviour. This includes older individuals with different levels of financial experience. Furthermore, the questionnaire may have included responses from individuals outside the specific Gen Z age, potentially affecting the accuracy of the findings. As such, the sample might not be able to represent the different status of the Malaysian population. Different educational level and employment status may have different perceptions. Hence, the findings might be more reflective of subgroup rather than the Gen Z population in Malaysia.

Thirdly, the data for this study is gathered all at once using a cross-sectional research approach. This makes it more difficult to document how user attitudes and technology adoption evolve over time. The evolution of financial technology and artificial intelligence is rapid, user perception toward AI tools may change significantly in the future. Therefore, the findings of this study may not fully reflect long-term behavioural patterns.

Moving on, this study focuses on users' perceptions of AI tools rather than their actual investment outcomes. Performance expectancy reflects the perceived usefulness of digital investment platforms. Nevertheless, it does not translate into real investment performance. Thus, there may be a gap between what users believe AI tools can achieve and their actual effectiveness. This limitation is critical because it suggests that positive perceptions of AI may not always correspond to improved returns or decision-making. Future studies could therefore overcome this constraint in order to offer a more thorough assessment of AI technologies in digital investment platforms.

Lastly, this study treats AI tools as generalised item rather than distinguishing between different types of AI functionalities such as robo-advisory, predictive analysis, and personalised recommendation systems. Each of these may influence users' perceptions and performance expectancy. Since this study does not differentiate between these specific AI applications, the depth of analysis may be limited, so the findings may not fully capture how different AI features uniquely affect user behaviour and technology adoption.

5.4 Recommendations

Several suggestions for further research can be made in light of the study's limitations. Firstly, future studies should extend the research framework by incorporating additional variables beyond those derived in this study. For instance, trust and perceived security are frequently included in extended frameworks like the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which may also be included in future studies to give a more thorough understanding of user behaviour regarding the performance expectations of new technologies.

Secondly, future studies can expand the sample beyond students aged 20 to 24 years with a Bachelor's Degree qualification to include Gen Z from different demographics such as from various other age groups, educational backgrounds, and employment statuses. By doing this, a more diverse and representative sample would provide a broader understanding on the different Gen Z behaviours towards digital investment platforms. Perhaps, future researchers may also consider cross-country comparisons to examine whether cultural and economic differences influence technology adoption and user's perception towards the performance expectancy of platforms from other countries.

Nevertheless, it is recommended that future studies use a longitudinal research design rather than a cross-sectional one. Since financial technology and AI evolve rapidly, a longitudinal research approach would allow researchers to capture changes in user perceptions, attitudes, and adoption behaviour over time. This approach would provide deeper insights into how users' trust and reliance on AI tools develop with experience.

Furthermore, future research should examine actual investment outcomes rather than relying solely on users' perceived performance expectancy. Researchers can better examine and assess the true effectiveness of AI tools in mediating digital investment platforms by incorporating measurable performances such as investment portfolio returns, accuracy, or risk management performance. This help bridge the gap between expected performance and actual performance.

Lastly, future studies should identify the various types of AI functionalities, such as robo-advisory services, predictive analysis, and personalised recommendation systems. This is due to different technologies may have different effects on user perceptions and adoption behaviour. Therefore, a more detailed and specific analysis would provide deeper insights into which specific AI features contribute most significantly to an increase or decrease in performance of digital investment platform.

The overall goal of these suggestions is to improve future research on AI's function in digital investing platforms in terms of its robustness, generalizability, and practical usefulness.

5.5 Conclusion

This study is centred to identify the variables affecting digital investment platform's performance expectations, with a particular emphasis on the function of artificial intelligence (AI) as a mediating variable. The research context, problem statement, research objectives, and research questions are outlined in Chapter 1, which also establishes the significance of the study. The Technology Acceptance Model (TAM) and Artificial Intelligence Device Use Acceptance (AIDUA) model were among the relevant theories and literature that were examined in the next chapter of Chapter 2. Additionally, hypotheses and a conceptual framework were established.

The research design, sample strategies, data collection methods, and SmartPLS 4.1.1.8 data analysis techniques were all covered in Chapter 3. This chapter made sure that appropriate techniques were employed to provide research findings that are consistent with the goals of the study. The data findings and analysis, on the other hand, were reported in Chapter 4. These included the study of the mediating variable, measurement model evaluation, structural model assessment, and descriptive analysis. These findings revealed the mediating function of AI as well as the significant and insignificant correlations between the independent and dependent variables.

The main conclusions, theoretical and practical ramifications, limitations, and suggestions for further research were all covered in Chapter 5. All things considered, this study advances our knowledge of how users interact with digital investment platforms and emphasises the role AI plays in mediating and influencing the performance expectations of new technological platforms. For researchers, practitioners, and platform developers looking to improve the efficacy and uptake of AI-driven technologies in the financial industry, this study offers insightful information.

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Appendices

Appendix I: Questionnaire

Performance Expectancy of AI Tools Mediating the Financial Investment Decisions: From the Perspective of Gen Z in Malaysia

Greetings, we are final-year students from Universiti Tunku Abdul Rahman (UTAR), currently pursuing Bachelor of Finance (Honours) programme. This questionnaire is conducted as part of our academic research requirements.

This questionnaire is part of an academic research study that aims to understand how performance expectancy of AI tools is mediating the financial investment decisions of Gen Z in Malaysia. Your participation will help provide valuable insights into how artificial intelligence influences investment decision-making and platform performance.

The questionnaire consists of **SEVEN (7) sections** and will take approximately **5–7 minutes** to complete.

Section A collects basic demographic information, such as age group, gender, etc.
Section B asks about your expectations regarding the performance and effectiveness of AI-powered digital investment platforms.
Section C - G focuses on your opinions and perceptions regarding factors such as social influence, ease of use, usefulness, hedonic motivation, and the role of artificial intelligence in digital investment platforms.

All responses are **anonymous and confidential** and will be used for academic purposes only.
There are no right or wrong answers, and you are encouraged to answer honestly based on your personal experience and opinions.

* Indicates required question

PERSONAL DATA PROTECTION STATEMENT

1. The purposes for which your personal data may be used are inclusive but not limited to:-

- For assessment of any application to UTAR
- For processing any benefits and services
- For communication purposes
- For advertorial and news
- For general administration and record purposes
- For enhancing the value of education
- For educational and related purposes consequential to UTAR
- For the purpose of our corporate governance
- For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

2. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

3. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

4. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

1. **Consent:** *

1. By submitting this form you hereby authorise and consent to us processing (including disclosing) your personal data and any updates of your information, for the purposes and/or for any other purposes related to the purpose.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at:
lwkitt04@1utar.my
lohjinlap@1utar.my
zhenhaoong@1utar.my

Mark only one oval.

- I have been notified by you and that I hereby understood, consented and agreed per UTAR above notice.
- I disagree, my personal data will not be processed.

Section A: Demographic Information

This section collects general background information to help understand the overall profile of respondents participating in this study. Your responses will be used only for academic analysis and will remain **confidential and anonymous**. There are no right or wrong answers. Please select the option that best represents your current situation.

2. Gender *

Mark only one oval.

- Male
- Female

3. Age Group *

Mark only one oval.

- 15 - 19
- 20 - 24
- 25 - 29
- 30 - 34
- 35 - 44
- 45 - 54
- 55 or older

4. Place of Residence * Dropdown

Mark only one oval.

- Johor
- Kedah
- Kelantan
- Kuala Lumpur
- Malacca
- Negeri Sembilan
- Pahang
- Perak
- Perlis
- Penang
- Sabah
- Sarawak
- Selangor
- Terengganu

5. Education Level *

Mark only one oval.

- High School
- College / Diploma
- Bachelor's Degree
- Master's Degree
- Doctorate / PhD

Section B: Performance Expectancy

Performance Expectancy refers to the degree to which you believe that using an AI-powered digital investment platform will help you achieve better investment performance and outcomes.

This section consists of **FIVE (5)** questions regarding the Performance Expectancy of Digital Investment Platforms (PE).

Kindly respond based on the scale:
1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

Using digital investment platform would help me accomplish financial goals more quickly. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I intend to keep using digital investment platform for making sustainable investment decisions. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I believe that using digital investment platform would increase my productivity. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I intend to use digital investment platform in the near future due to its performance. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section C: Social Influence

Social Influence refers to the degree to which
an individual is influenced by others in believing he or she should adopt the technology during the process of technology acceptance.

This section consists of **FOUR (4)** questions regarding the influence of Social Influence (SI) towards the Performance Expectancy of Digital Investment Platforms (PE).

Kindly respond based on the scale:
1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

People who are important and who can influence my behaviour think that I should use digital investment platform. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Financial experts and mentors I follow encourage the use of digital investment platforms. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

My peers believe that digital investment platforms are beneficial for making financial decisions. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Most people in my social circle (e.g., friends, colleagues) use digital investment platforms to support their investment. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section D: Perceived Usefulness

Perceived Usefulness is the degree to which an individual believes that using a certain system will probably improve their job performance or assist them to achieve their goals.

This section consists of **FIVE (5)** questions regarding the influence of Perceived Usefulness (PU) towards the Performance Expectancy of Digital Investment Platforms (PE).

Kindly respond based on the scale:
1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

The digital investment platform can improve the overall performance of my sustainable investment portfolio. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I believe that the digital investment platform provides useful insights into sustainable investment opportunities. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

The digital investment platform is useful in aligning my investment strategy with sustainability. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Using digital investment platform would improve my investment performance and productivity. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section E: Perceived Ease of Use

Perceived Ease of Use is the extent to which an individual
perceives a system as simple to operate and require minimal cognitive effort.

This section consists of **FIVE (5)** questions regarding the influence of Perceived Ease of Use (PEU) towards the Performance Expectancy of Digital Investment Platforms (PE).

Kindly respond based on the scale:
1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

I would find it easy to get digital investment platform to do what I want it to do. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I would find digital investment platform to be flexible to interact with. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

It would be easy for me to become skilful at using digital investment platform. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I would find digital investment platform easy to use. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section F: Hedonic Motivation

Hedonic Motivation refers to the willingness to
initiate actions or behaviours which enhance the positive experience (pleasure)
and reduces the negative experience (pain).

This section consists of **FOUR (4)** questions regarding the influence of Hedonic Motivation (HM) towards the Performance Expectancy of Digital Investment Platforms (PE).

Kindly respond based on the scale:
1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

Using digital investment platform is fun. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Using digital investment platform is enjoyable. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I enjoy using digital investment platforms because they make my investment experience more fun and engaging. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I find it exciting to interact with digital investment platforms as it adds an element of novelty to my investing experience. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Section G: Artificial Intelligence

Artificial Intelligence refers to intelligent systems embedded within digital investment platforms, such as robo-advisors, predictive analytics, and automated recommendations, that support investment decision-making.

This section consists of **FIVE (5)** questions regarding the influence of Artificial Intelligence (AI) towards the Performance Expectancy of Digital Investment Platforms (PE).

Kindly respond based on the scale:
1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

My general knowledge about AI is more than sufficient compared to many. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Learning and implementing innovations in AI applications are a priority for me. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

I take pleasure in using artificial intelligence applications. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Learning artificial intelligence applications is an easy task for me. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Thank You

Thank you very much for taking the time to complete this questionnaire. Your participation is greatly appreciated and contributes significantly to the success of this academic research.

All information provided will be kept strictly confidential and used solely for academic purposes. Your responses will help improve understanding of how Generation Z investors in Malaysia perceive and adopt AI-powered digital investment platforms.

If you have any questions regarding this study, please feel free to contact the researchers.

Once again, thank you for your valuable time and support.

Please click "Submit" to complete the survey.

Appendix II: Central Tendencies and Dispersion Measurement of Construct

Indicators

Copy to Excel/Word

Name	No.	Type	Missings	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
Gender	1	TEXT	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age Group	2	TEXT	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Place of Residence	3	TEXT	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Education Level	4	TEXT	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PE1	5	MET	0	3.791	4.000	1.000	5.000	1.000	5.000	0.968	-0.183	-0.608	0.000
PE2	6	MET	0	3.747	4.000	1.000	5.000	1.000	5.000	0.986	-0.363	-0.534	0.000
PE3	7	MET	0	3.783	4.000	1.000	5.000	1.000	5.000	1.017	0.146	-0.712	0.000
PE4	8	MET	0	3.758	4.000	1.000	5.000	1.000	5.000	1.015	0.009	-0.656	0.000
SI1	9	MET	0	3.642	4.000	1.000	5.000	1.000	5.000	0.995	-0.357	-0.563	0.000
SI2	10	MET	0	3.609	4.000	1.000	5.000	1.000	5.000	0.999	-0.237	-0.483	0.000
SI3	11	MET	0	3.621	4.000	1.000	5.000	1.000	5.000	1.006	-0.127	-0.527	0.000
SI4	12	MET	0	3.572	4.000	1.000	5.000	1.000	5.000	1.030	-0.237	-0.452	0.000
PU1	13	MET	0	3.774	4.000	1.000	5.000	1.000	5.000	0.952	-0.116	-0.535	0.000
PU2	14	MET	0	3.715	4.000	1.000	5.000	1.000	5.000	1.040	-0.180	-0.594	0.000
PU3	15	MET	0	3.700	4.000	1.000	5.000	1.000	5.000	1.015	-0.261	-0.469	0.000
PU4	16	MET	0	3.722	4.000	1.000	5.000	1.000	5.000	1.024	-0.137	-0.585	0.000
PEOU1	17	MET	0	3.720	4.000	1.000	5.000	1.000	5.000	0.991	-0.363	-0.566	0.000
PEOU2	18	MET	0	3.673	4.000	1.000	5.000	1.000	5.000	0.888	-0.133	-0.514	0.000
PEOU3	19	MET	0	3.655	4.000	1.000	5.000	1.000	5.000	1.023	-0.082	-0.555	0.000
PEOU4	20	MET	0	3.711	4.000	1.000	5.000	1.000	5.000	0.976	-0.123	-0.515	0.000
HBB1	21	MET	0	3.751	4.000	1.000	5.000	1.000	5.000	0.972	-0.060	-0.572	0.000
HBB2	22	MET	0	3.706	4.000	1.000	5.000	1.000	5.000	1.010	-0.047	-0.619	0.000
HBB3	23	MET	0	3.601	4.000	1.000	5.000	1.000	5.000	1.061	-0.236	-0.507	0.000
HBB4	24	MET	0	3.621	4.000	1.000	5.000	1.000	5.000	1.060	-0.183	-0.581	0.000
AI1	25	MET	0	3.700	4.000	1.000	5.000	1.000	5.000	0.997	-0.465	-0.423	0.000
AI2	26	MET	0	3.749	4.000	1.000	5.000	1.000	5.000	0.993	-0.244	-0.559	0.000
AI3	27	MET	0	3.695	4.000	1.000	5.000	1.000	5.000	1.036	-0.060	-0.631	0.000
AI4	28	MET	0	3.720	4.000	1.000	5.000	1.000	5.000	1.020	-0.028	-0.636	0.000

Appendix III: Outer Loadings

Outer loadings - Matrix

	AI	HM	PE	PEOU	PU	SI
AI1	0.710					
AI2	0.767					
AI3	0.682					
AI4	0.702					
HM1		0.665				
HM2		0.786				
HM3		0.828				
HM4		0.794				
PE1			0.737			
PE2			0.725			
PE3			0.707			
PE4			0.671			
PEOU1				0.725		
PEOU2				0.750		
PEOU3				0.728		
PEOU4				0.730		
PU1					0.765	
PU2					0.758	
PU3					0.712	
PU4					0.745	
SI1						0.624
SI2						0.763
SI3						0.732
SI4						0.737

Outer loadings - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI1 <- AI	0.710	0.710	0.027	25.829	0.000
AI2 <- AI	0.767	0.766	0.024	31.559	0.000
AI3 <- AI	0.682	0.681	0.033	20.522	0.000
AI4 <- AI	0.702	0.701	0.033	21.481	0.000
HM1 <- HM	0.665	0.664	0.037	17.984	0.000
HM2 <- HM	0.786	0.785	0.021	37.234	0.000
HM3 <- HM	0.828	0.827	0.017	48.905	0.000
HM4 <- HM	0.794	0.794	0.017	45.598	0.000
PE1 <- PE	0.737	0.737	0.025	29.143	0.000
PE2 <- PE	0.725	0.724	0.028	25.869	0.000
PE3 <- PE	0.707	0.706	0.031	22.788	0.000
PE4 <- PE	0.671	0.670	0.034	19.943	0.000
PEOU1 <- PEOU	0.725	0.724	0.030	24.472	0.000
PEOU2 <- PEOU	0.750	0.749	0.027	27.895	0.000
PEOU3 <- PEOU	0.728	0.727	0.029	24.855	0.000
PEOU4 <- PEOU	0.730	0.730	0.025	28.794	0.000
PU1 <- PU	0.765	0.765	0.022	34.864	0.000
PU2 <- PU	0.758	0.757	0.026	29.652	0.000
PU3 <- PU	0.712	0.711	0.028	25.451	0.000
PU4 <- PU	0.745	0.744	0.027	27.852	0.000
SI1 <- SI	0.624	0.623	0.042	15.044	0.000
SI2 <- SI	0.763	0.762	0.026	29.621	0.000
SI3 <- SI	0.732	0.732	0.026	27.876	0.000
SI4 <- SI	0.737	0.737	0.027	27.201	0.000

Appendix IV: Construct Reliability and Validity

Construct reliability and validity - Overview   Copy to Excel/Word   Co

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (A...
AI	0.683	0.688	0.808	0.512
HM	0.771	0.785	0.853	0.594
PE	0.672	0.674	0.803	0.505
PEOU	0.714	0.714	0.823	0.538
PU	0.733	0.735	0.833	0.555
SI	0.683	0.692	0.807	0.513

Appendix V: Cronbach's Alpha

Cronbach's alpha - Mean, STDEV, T values, p values   Copy to Excel/Word   Co

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI	0.683	0.682	0.030	22.849	0.000
HM	0.771	0.770	0.021	37.475	0.000
PE	0.672	0.670	0.033	20.267	0.000
PEOU	0.714	0.712	0.026	27.191	0.000
PU	0.733	0.732	0.024	30.654	0.000
SI	0.683	0.682	0.028	24.205	0.000

Appendix VI: Average Variance Extracted

Average variance extracted (AVE) - Mean, STDEV, T values, p values

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	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI	0.512	0.513	0.023	21.890	0.000
HM	0.594	0.594	0.021	27.841	0.000
PE	0.505	0.505	0.025	20.335	0.000
PEOU	0.538	0.537	0.023	23.780	0.000
PU	0.555	0.555	0.022	25.361	0.000
SI	0.513	0.513	0.022	23.289	0.000

Appendix VII: Heterotrait-Monotrait Ratio

Discriminant validity - Heterotrait-monotrait ratio (HTMT) - Matrix

	AI	HM	PE	PEOU	PU	SI
AI						
HM	0.757					
PE	0.976	0.833				
PEOU	0.828	0.757	0.875			
PU	0.892	0.689	1.012	0.779		
SI	0.753	0.800	0.919	0.725	0.818	

Appendix VIII: Collinearity

Collinearity statistics (VIF) - Inner model - List

	VIF
AI -> PE	2.046
HM -> AI	1.818
HM -> PE	1.889
PEOU -> AI	1.762
PEOU -> PE	1.876
PU -> AI	1.808
PU -> PE	2.060
SI -> AI	1.843
SI -> PE	1.859

Appendix IX: Path Coefficient

Path coefficients - Mean, STDEV, T values, p values

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	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI -> PE	0.213	0.213	0.050	4.211	0.000
HM -> AI	0.187	0.188	0.057	3.290	0.001
HM -> PE	0.142	0.141	0.051	2.778	0.005
PEOU -> AI	0.236	0.234	0.063	3.774	0.000
PEOU -> PE	0.122	0.124	0.046	2.631	0.009
PU -> AI	0.351	0.351	0.059	5.992	0.000
PU -> PE	0.329	0.329	0.052	6.373	0.000
SI -> AI	0.089	0.091	0.056	1.585	0.113
SI -> PE	0.181	0.181	0.044	4.079	0.000

Appendix X: R Square

R-square - Overview

	R-square	R-square adjusted
AI	0.511	0.507
PE	0.649	0.645

R-square - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI	0.511	0.519	0.039	13.008	0.000
PE	0.649	0.656	0.033	19.540	0.000

R-square adjusted - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI	0.507	0.515	0.040	12.780	0.000
PE	0.645	0.652	0.034	19.202	0.000

Appendix XI: F Square

f-square - Matrix

	AI	HM	PE	PEOU	PU	SI
AI			0.063			
HM	0.039		0.030			
PE						
PEOU	0.065		0.023			
PU	0.139		0.149			
SI	0.009		0.050			

Appendix XII: Q Square

PLSpredict LV summary - PLS-SEM

	Q^2predict	RMSE	MAE
AI	0.494	0.716	0.523
PE	0.615	0.624	0.466

Appendix XIII: Mediation Analysis

Total indirect effects - Mean, STDEV, T values, p values

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	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
HM -> PE	0.040	0.040	0.016	2.481	0.013
PEOU -> PE	0.050	0.049	0.016	3.072	0.002
PU -> PE	0.075	0.075	0.023	3.287	0.001
SI -> PE	0.019	0.020	0.014	1.402	0.161