UNIVERSITY STUDENTS' INTENTION TO ADOPT ARTIFICIAL INTELLIGENCE (AI) TOOLS IN INVESTMENT STRATEGIES: EVIDENCE FROM UNIVERSITY TUNKU ABDUL RAHMAN

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of my own work and that dueacknowledgement has been given in the references to ALL sources of informationbe they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any applicationfor any other degree or qualification of this or any other university, or other institutes of learning.

(3) The word count of this research report is__24636_________.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANOVA	Analysis of Variance
ARIMA	Auto Regressive Integrated Moving Average
ASPAC	Asia-Pcific
ATT	Attitude
BGLM	Bayesian Generalised Linear Models
BI	Behavioral Intention
CCA	Computer Crimes Act 1997
DIM	Digital Investment Managers
DL	Deep Learning
DOI	Diffusion of Innovation Theory
EE	Effort Expectancy
ETFs	Exchange-Traded Funds
FAM	Faculty of Accountancy and Management
FC	Facilitating Condition
Fintech	Financial Technology
FRAs	Financial Robo-Advisors
FSA	Financial Services Act 2013
GNDR	Gender
GRU	Gated Recurrent Unit
GTB	Gradient Tree Boosting
HA	Habit
HM	Hedonic Motivation
IDT	Innovation Diffusion Theort
IFSA	Islamic Financial Services Act 2013

IPOs	Initial Public Offerings
IPSR	Institute of Postgraduate Studies and Research
IT	Information Technology
JASP	Jeffreys's Amazing Statistics Program
KDI	Kenaga Digital Investing
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MyDIGITAL	Malaysia Digital Economy Blueprint
NAIO	National AI Office
NLP	Natural Language Processing
P	Price Value
PDPA	Personal Data Protection Act
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PhD	Doctor of Philosophy
PU	Perceived Usefulness
R^2	Coeeficients of Determination
RMiT	Risk Management in Technology Policy Document
RMSE	Root Mean Squared Error
RPA	Robotic Management in Technology
SE	Standard Error
SI	Social Influence
SMEs	Small and Medium-sized Enterprises
SPSS	Statistical Package for the Social Sciences
SVM	Support Vector Machines
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reason Action

U.S./USA	United Status
UAE	United Arab Emirates
UTAR	University Tunku Abdul Rahman
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
WBSNs	Web-based Social Networks
YRIs	Young Retailer Investors

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ABSTRACT

This study examines the factors influencing the behavioral intention of University Students to adopt Artificial Intelligence (AI) in investment strategies, which is focused on Universiti Tunku Abdul Rahman. This study aims to find out what the main factors are that influence behavioral intention to adopt the AI investment tool. Under this current study, the theory used is the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) to investigate the important determinants involved in these two theories, excluding the performance expectancy and effort expectancy. Demographic variables (Gender) also serve as independent variables of this study. A quantitative method was utilised to evaluate the hypothesis. According to this, data were collected from UTAR students using the closed-ended questionnaire. The gathered data were analysed using Statistical Package for the Social Sciences (SPSS). This study offers valuable insights to the Fintech service providers, financial institutions and government.

CHAPTER 1: INTRODUCTION

1.0 Research Background

In computer science, artificial intelligence (AI) is the research of creating systems that are capable not only of learning and reasoning, but also of solving problems such as humans. The understanding of AI has been developing for decades as its founders, like Alan Turing, began to respond to those questions in the 1940s. It was summed up with the official presentation of AI at the Dartmouth Conference in 1956. Although there was some initial optimism, AI ended up being a problem because it was limited in these areas of power and the feasible range of rule-based systems. Nevertheless, AI transformed towards the end of the 20th century, with the introduction of data-driven methods, machine learning and neural networks into the field (History and Evolution of Artificial Intelligence | AI Timeline Explained, 2023). Hence, the evolution of AI is not only can described as technology but also a societal since it can use to redefine the relationship between individuals and the organization that possess expertise, services and decision-making.

Globally, AI has become a key component of digital transformation and has attracted much private funding and policy interest. According to Dipert (2025), global AI adoption is predicted to increase by another 20% and reach 378 million users in 2025. Statista Market Insight also reported that the number of AI users worldwide continued to increase from 115.9 million to 154.3 million in 2021. This upward trend is maintained with 47.1 million new users in 2022 and 53.4 million in 2023. In 2024, the AI adoption is boosted by 59.6 million users in 2024, reaching 314.4 million worldwide. The forecaster has also estimated that the new users will rise by 64.4 million. It can bring the total number of users to almost 378.8 million in 2025. This growing situation is further proven by Statista, which estimated that the adoption rate of AI will reach approximately 730 million users by 2030. The rapid growth underscores AI's transition from an emerging technology to an industry-standard tool that is incorporated into daily life (Dipert, 2025).

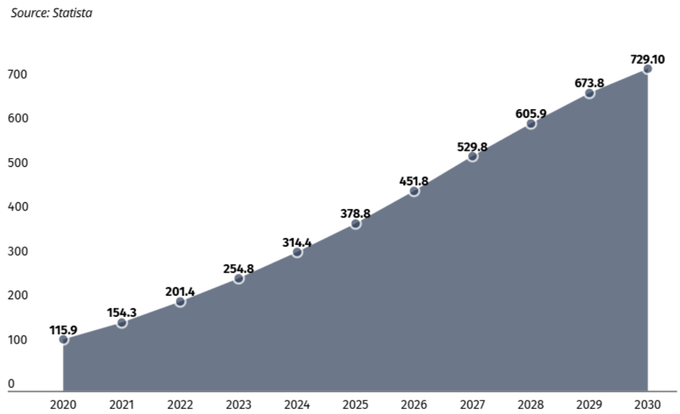


Figure 1: AI investment user rate in the global (Dipert, 2025).

Since the demand for AI adoption has increased, it has boosted global AI investment. Referring to the AI Index Report 2025, that conducted by Stanford University (2025), artificial intelligence is obtaining global attention that has attracted huge financing. The global corporate AI investment reached USD 252.3 billion in 2024, which is a 25.5% increase from 2023. The main driver of this growth is due to the rise of 44.5% in private investment, while mergers and acquiring increased by 12.1%. Over the past decade, AI-related investments have grown around three times, reflecting that the technology is essential to business and government strategies. In other words, AI today is viewed as a core tool to drive the business and national competitiveness rather than experimental technology.

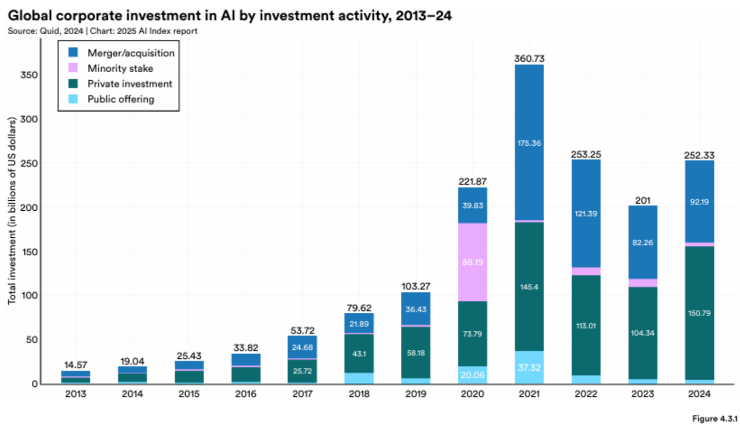


Figure 2: Global corporate investment in AI by investment activity (Njenga Kariuki, 2025)

From a regional perspective, the United States was a dominant global investor in AI. In 2024, the U.S. invested USD 109.1 billion in private AI (see figure 2). This investment is 12 times greater than China, who invest USD 9.3 billion. In the meantime. US investment in AI is 24.1 times greater than the United Kingdom's USD 4.5 billion. Other important contributors included Sweden (USD 4.3 billion), Austria (USD 1.5 billion), the Netherlands (USD 1.1 billion), and Italy (USD 0.9 billion).

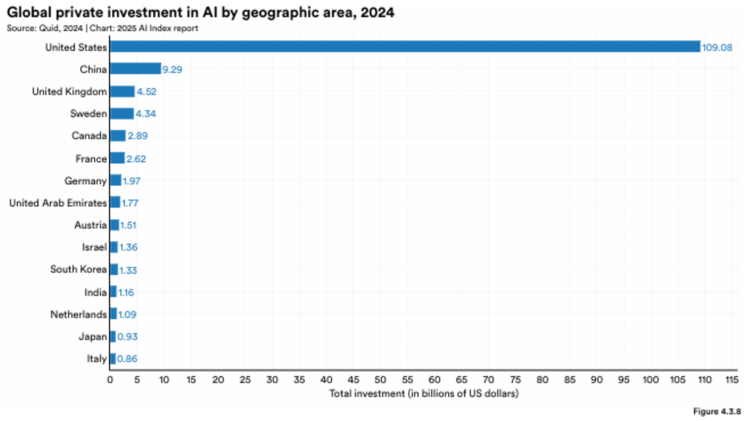


Figure 3: Global private investment in AI geographic area (Njenga Kariuki, 2025)

The rise in AI adoption has also reformed the financial sector, particularly in investment management. In fact, the incorporation of AI into investment strategies is no longer a recent development. An AI in Investment Management Survey (2024) shows that 150 asset managers found that 91% are either currently using (54%) or intend to use (37%) the AI. Big data analysis (40%), idea generation (32%), and identifying alternative data signals (31%) are the commonly used applications, while adoption in risk management (14%) and trading processes (10%) remains limited. These findings reveal that AI is becoming an important decision-support tool, but its role that plays in investment execution is still in the early stages.

Nonetheless, according to the AI Index Report 2025 by Stanford University (2025), the financial sector ranks only fifth among industries in global AI investment, reflecting a slower pace of adoption compared to other sectors. KPMG (2024) further proves that the companies in North America, ASPAC and Europe are increasingly exploring AI in financial planning. But, its adoption is still limited, as evidenced by only 10% of firm managers reporting wide adoption, and 23% reporting selective adoption. The majority are still in the early stages, with 30% piloting 28% are merely planning, and 9% having no plans at all. This demonstrates that AI in finance remains in the early stages of integration regarding its benefits. In addition to that, the fraud case of AI startup founder Albert Saniger, who had raised around USD$27 million before the company failed, demonstrates how a lack of trust in AI can be undermined by misinformation and overblown promises (U.S. Department of Justice, 2024).

Focusing on Malaysia, it has also achieved key advances in the implementation of artificial intelligence (AI) in the public and private sectors, which contribute to the economic growth and innovations of the country. As evidence, the AI investment has been on the increase in Malaysia, where the country's pipeline has reached up to RM59.1 billion in 2025 (Mail, 2025). To further support this fact, the Malaysian government also introduced a regional AI hub, called the National Artificial Intelligence Action Plan (2026-2030) and National AI Office (NAIO), to encourage the national AI ecosystem (Malaysia Sets Sight on Regional AI Leadership With 2026-2030 Action Plan, 2025*)*. While the NAIO is conducted based on the development of the AI Technology Action Plan 2026-2030 to create an AI regulation system framework and code of ethics, conducting impact studies at the government level, as well as developing datasets on AI (Doria, 2025). Furthermore, the Malaysia Digital Economy has actively collaborated with local AI providers to promote the AI ecosystem in Malaysia (Loheswar, 2024). All the initiatives are in line with the Malaysia Digital Economy Blueprint (MyDIGITAL), which outlined the importance of adopting AI to drive the nation to transform into a technology-driven economy.

Despite these advancements, 84% of Malaysian companies are still in an exploratory stage of AI adoption. Although most of them are only aware of and investigating AI’s potential, but they have not deeply integrated AI into their operations (Jamaludin.Mk, 2025). At the same time, public concerns remain high. To prove that, 60% of Malaysians worry about the misuse of personal data by AI-integrated devices. In response, the government has established several regulations, such as the Personal Data Protection Act (PDPA), Risk Management in Technology (RMiT) Policy Document, Financial Services Act (FSA) 2013, Islamic Financial Services Act (IFSA) 2013, Digital Signature Act 1997, and the Computer Crimes Act 1997 (CCA*)* to protect the personal data of the consumer from being breached by hackers and ensure fair practices. However, Malaysia has no specific law or regulation directly addressing artificial intelligence (AI). Without concert AI governance frameworks, implementation standards remain inconsistent.

Some recent fintech and investment firms in Malaysia have already begun integrating AI tools into their investment offerings. Strong evidence is the rise of licensed robo-advisor platforms, formally known as Digital Investment Managers (DIM), which are regulated by the Securities Commission under Malaysia's DIM framework. These platforms employ algorithms to construct and manage personalized portfolios for retail investors. For example, MYTHEO, StashAway, and Wahed Invest are offering simplified, low-cost access to investing while lowering the entry barriers associated with traditional wealth management. The emergence of robo-advisors provides a tangible example of how AI is reshaping investment strategies in Malaysia (Tan, 2025). Other than that, RHB Asset Management has collaborated with Qraft Technologies to launch the RHB Dynamic Artificial Intelligence Allocator Fund, which is Malaysia's first AI-driven multi-asset fund backed by a bank-asset manager. This fund uses AI models trained on over 80 datasets (including macroeconomic and technical signals) to forecast volatility and rebalance between asset classes monthly, even including digital assets (Craft and RHB Asset Management Launch Malaysia's First AI-based Multi-asset Fund, 2025). Meanwhile, Kenanga's *Kenanga Digital Investing (KDI)* platform provides a fully automated robo-advisor service, which includes two offerings (*KDI Save* and *KDI Invest)*. It uses AI algorithms to monitor global market conditions and reallocate portfolios automatically based on risk preferences. Besides, this platform also offers investment access via global ETFs and competitive fees to the investor (Bernardng, 2024).

On the other hand, AI adoption in Malaysia's financial sector is still limited due to several challenges. For instance, many companies are experiencing a lack of talented AI professionals, with 81% of them stating that they were having issues with recruiting talent despite 90% of them admitting that AI is a business priority (Rajaendram, 2025). Another problem is that financial institutions have trouble integrating their disparate data platforms. The regulatory uncertainties regarding data privacy, cybersecurity, and ethical use further slow down the adoption. These issues show that financial institutions must deal with structural gaps and work within flexible regulatory systems to maximise the benefits of AI in banking and investment (Mail, 2025). These limitations are likely to clarify why many individuals, especially young investors in Malaysia, remain cautious about adopting AI in making financial decisions.

Generation Z, who were born mid-1990s to early 2000s (Alkadi and Abed, 2025), is first generation to have grown up with constant access to digital technology and AI-powered services. These demographics, including university students (McCrary, 2025) prefer to use AI technologies because they value visual learning, rapid information access, and multitasking (Boon Lim et al., 2025; De Jong McKenzie, 2025). It has encouraged young investors active in investment markets by using AI. The COVID-19 pandemic helped accelerate this trend by creating excess capital and encouraging them to explore investment through online communities, financial instruments and social media (Bashir et al., 2025). Today, Gen Z (including UTAR students) often faces financial pressure like higher education costs, uncertain employment opportunities, and restricted access to cheaper housing prices. This situation further motivated them to explore innovative financial solutions such as AI-based investment tools.

Nevertheless, according to the Schoeff (2023), who has surveyed generative AI (including young investors), found that 21% perceive AI as a threat to their careers. While 31% consider it a threat to the advice sector overall. Even youthful investors are generally receptive to new technology, some professional advisers indicate that they may also have uncertainty when utilising AI-driven investment tools, resulting in poor adoption patterns. Therefore, this study highlights the need to investigate young investors' behavioral intention towards AI tools (especially for financial management), meaning this study is focused on examining their willingness to adopt AI investment tools.

1.1 Definition of Key Term AI-enabled tools

AI-enabled tools have offered personalised recommendations and customisation content to the users, which transformed their experiences. Simply put, AI tools are the technologies that enable computers and machines to think and behave like humans. According to UMATechnology (2025), AI tools are software system that uses artificial intelligence to perform tasks that were previously done by humans. For example, using machine learning to learn from data, natural language processing to understand and generate human language, computer vision to read text, and robotic process automation to automate rule-based procedures. Resume screening software is an AI tool that can quickly scan hundreds of job applications and find the best applicants by analyzing keywords, experience, and skills (Naik, 2025).

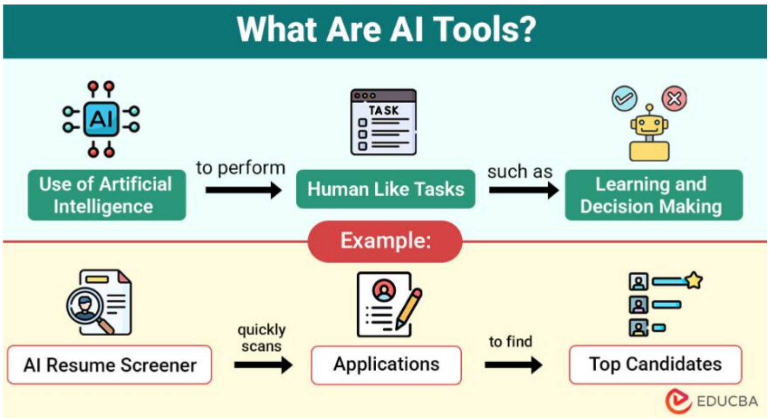


Figure 4: Explanation of AI tools (Naik, 2025).

It involved various types, such as Natural Language Processing (NLP) for chatbots and translations, Machine Learning platforms for forecasting models, Computer Vision for image or video analysis, Robotic Process Automation (RPA) for automating daily tasks and AI content generation tools for text code and art. Popular examples are ChatGPT, Google Cloud AI, UiPath, TensorFlow, and Canva's AI. However, utilisation of the AI tools remains some challenges like data privacy, biased job, job displacement, and complexity. Today, AI tools are widely used in daily life, from virtual assistants like Siri and Alexa to platforms like Netflix and Amazon that analyze user preferences and behaviors to deliver personalized recommendations (Arhip, 2024).

AI tools in the financial sector are considered platforms or applications that improve financial tasks such as analysis, forecasting, planning, budgeting, and auditing. Unlike traditional tools, AI-enabled financial applications can leverage both historical and real-time data to discover patterns, abnormalities, and generate accurate forecasts. In this way, the assist finance teams to become more efficient, error-free, and more active and data-driven in their choices and behavior (AI Tools for Finance, 2025), and economize (Naik, 2025). Example AI investment platforms that are famous among Malaysian investors are MooMoo, Kenaga Digital Investing (KDI), MYRHEO

1.2 Problem Statement

Artificial Intelligence (AI) has become a crucial part of the global financial ecosystem. This is due to it can help in revolutionising procedures like risk evaluation, portfolio management and investment decision-making. It also plays a useful role in improving financial services, accessibility, accuracy, dependability and efficiency as it can process a large amount of data automatically and predict future information (Supermicro, 2024). In Malaysia, AI-driven innovations are also starting to impact the investment strategies among investors. As an illustration, Kenaga had launched a fully automated robo-advisor investment platform while RHB introduced the AI-powered multi-asset allocater fund. Nonetheless, the adoption of these AI-driven investment tools is still at an early stage in Malaysia. The factors such as limited awareness (Jamaludin. M.K., 2025), talent shortages, fragmented data systems and absence of clear AI regulation (Doria, 2025), leading to a narrow willingness of investors to use these tools.

Majority of the past research on AI adoptions has concentrated on forecasting users' intention to use AI tools, especially robo-advisors. For instance, they had investigate trust and performance expectations between humand advisors and robo-advisors (Zhang et al., 2021); the experience of dealing with robo-advisors (Belanche et al., 2020; Jung et al., 2018a; Hildebrand & Bergner, 2021; Hohenberger et al., 2019; Seiler & Fanenbruck, 2021; Wu & Gao, 2021), and the users' trait for the robo-advisor (Fulk et al., 2018; Cheng, 2021). Despite all these studies having provided useful and meaningful insight into what factors impact the intention of adopting new technologies, most of them have focused on other countries such as Indonesia (Zhafira et al., 2025; Pusposari et al., 2024; Nainggolan & Handayani, 2023), India (Dixit et al., 2025; Marak et al., 2025), China (Du et al., 2025; F. Wang et al., 2023c), and the United States (J. Park et al., 2024), rather than Malaysia. Plus, many existing studies had examined behavioral intention to adopt the AI tools that mainly focused on other industries like education and healthcare, compared to the financial sector. Additionally, few studies have examined the behavioral intentions of young investors. These problems have left a gap in understanding how the young investor in Malaysia's intentions are affected.

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT2) are widely applied to explain technology adoption. Under TAM, Perceived usefulness and Perceived Ease of Use have also been proven as significant variables in affecting the intention of using AI tools (Belanche et al., 2019; Nainggolan & Handayani, 2023; Wu & Chen, 2016; Almajali et al., 2022). However, testing only these two constructs often fails to provide a comprehensive understanding of the actual behavior (AlAmayreh et al., 2023) and does not consider the social influence (Atwal & Bryson, 2021). This prompts most researchers to expand TAM with other theories, such as TRA (Belanche et al., 2019; Almajali et al., 2022), IDT (Mollel & Chen, 2025), TPB (Nainggolan & Handayani, 2023), trust (De Blanes Sebastián et al., 2022), and others. In this study, TAM serves as the primary theoretical framework, expanded with UTAUT2 to form an integrated model that has not yet been fully tested in technology adoption research.

UTAUT2 incorporates a wide range of variables, such as hedonic motivation and social influence, which enable researchers to measure how emotions and the opinions of others affect users' decisions to adopt financial robo-advisory services. The increases in the variable represent that most of the factors have been included to test the behavioral intention of users, which can lead to a high accuracy of the result. This idea can be further confirmed by Venkatesh et al. (2016), who said UTAUT2 shows better predictive accuracy because it accounts for 74% of consumer behavior patterns and 52% of technology adoption patterns compared to

TAM. Despite this, previous studies have produced inconsistent findings regarding constructs such as facilitating conditions, social influence, habit, hedonic motivation, and price value, leaving the actual relationships between these factors and behavioral intention unclear. Additionally, demographic variables such as age, gender are often treated as control variables rather than independent variables. This leaves their influence on adoption behaviors underexplored.

Therefore, this study focuses on young investors (UTAR students) since they might shape the future investment industry trend of Malaysia. Understanding their attitudes and intentions towards AI-enabled investment tools is essential, as it can influence the long-term growth of the economy and financial technology in the country. Overall, this study will seek to identify the key factors that impact the UTAR students' attitudes and behavioral intention to provide useful insights for both academic and financial institutions or even the government.

1.3 General Objectives

This study aims to investigate and explore the young investors' behavioural intention in utilizing the AI-enabled tools for their investment strategies with evidence from Universiti Tunku Abdul Rahman (UTAR) students. Conducting this research is also to examine the perceptions, attitudes, and awareness of the UTAR students regarding the AI-enabled investment tools. By including demographic characteristics like gender and stream, it can provide insight into how different genders and the knowledge that an individual learns will influence their perceptions of AI tools. Then, the final objective of this paper is to establish appropriate implications for financial service providers, educators, and policymakers to enhance the adoption of AI tools in investment strategies. The following research questions were developed based on the research objectives:

i. To investigate the factors that influence UTAR students' attitudes towards AI-driven investment tools

ii. To examine the factors that shape UTAR students' behavioral intention to adopt AI-based investment tools.

1.4 Specific Objectives:

Below are the specific objectives of this research:

i. To examine the influence of perceived usefulness on students' attitudes to use AI tools in investment strategies;
ii. To analyse the effect of perceived ease of use on the attitude towards AI-driven investment tools;
iii. To investigate the impact of facilitating conditions on the attitude of students towards adopting AI investment tools;
iv. To evaluate the role of social influence in shaping students' attitudes toward AI tools for investment;
v. To determine the effect of price value on students' behavioral intention toward AI-driven investment tools;
vi. To assess how habit influences students' intention of AI investment tools;
vii. To measure the effect of hedonic motivation on students' behavioral intention to adopt AI-driven tools for investment;
viii. To test how the attitude influences students' behavioral intention to adopt AI investment tools.
ix. To explore the influence of demographic factors (gendeR) on students' intention to use AI investment tools; and

1.5 Research Questions:

To achieve the objectives outlined above, this study formulates several research questions aimed at addressing the key gaps in understanding young investors' adoption of AI-driven investment tools.

i. What are the factors that influence UTAR students' attitudes towards AI-driven investment tools?
ii. What are the factors that shape UTAR students' behavioral intention to adopt AI-based investment tools

1.6 Significance of the Study

Understanding the behavioral intention and attitude of the young investors towards the AI investment tools is crucial because the young generations often represent the next wave of investors, which might shape both national and financial industry future market conditions and landscape. With the growing integration of AI tools into the financial ecosystem, the paper's findings can offer valuable insights to help students strengthen their financial literacy, cultivate early and responsible investment habits, and make more informed decisions. In turn, these outcomes can contribute to improved long-term financial well-being at the individual level while supporting the sustainable growth and competitiveness of the financial industry and fostering informed decisions.

The second importance of this research is that it can offer practical implications for the financial institutions, especially the firms that plan to offer AI investment tools in the future. Since this study analysed many factors, such as behavioral, social, emotional, price, and interface-friendly, it provides the possible barriers and motivations used in AI tools among young generations. Therefore, this can assist in tailoring marketing strategies; ultimately, the financial services providers or fintech developers can design customer-centered AI investment platforms and applications with expectations of users, particularly the young generations. As a result, this can strengthen user confidence, improve satisfaction, and enhance the long-term adoption and success of AI-driven financial innovations.

According to the academic sector, this study contributes to future research on the integration frameworks of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT2) while extending the framework with demographic characteristics. This hybrid framework allows for a more comprehensive exploration of behavioral intentions compared to models that focus only on limited constructs. Testing demographic variables such as gender and academic stream can show whether differences in gender and academic knowledge can lead to different decisions decision-making in the adoption of AI investment tools. Moreover, it not only addresses a significant geographical and generational gap in existing studies but also provides a framework that can be replicated or refined by future researchers.

1.7 Scope of the Study

This ongoing research will focus on the adoption and use of AI-enabled investment tools among young investors, which will lead to a study of the behavioral intention and attitude of UTAR students toward these technologies. The present study primarily focuses on the determinants of young investors' behavioural intention to adopt AI investment tools.

The primary objective of this study is to investigate the relationships among the attitude towards AI-based investment tools adoption of UTAR students and the Perceived Usefulness, Perceived Ease of Use, Social Influence, as well as Facilitating Conditions. Additionally, it examines the factors that affect the behavioural intentions to adopt these tools among UTAR students. The population of the study is concentrated on Malaysian young investors, as they represent a critical stage where students begin to develop financial awareness and exposure to investment opportunities. Then, the sample of this study consists of all UTAR students who are currently in Year 2 Semester 3 (Y2S3) and Year 3 Semester 1 (Y3S1).

The study is geographically limited to UTAR campuses (either at Kampar or Sungai Long) and does not restrict to professional investors. This is because this study measures the students' behavioral intention rather than the actual investment performance. Overall, the research aims to provide an insight into the current mindset of young Malaysian investors toward the adoption of AI-based investment tools through the perspective of UTAR students.

1.8 Organisation of the study

This research is structured into 5 chapters to provide a clear presentation of the study. Chapter 1 has introduced the background of the study, key terms' definition, research problem, objectives, research questions, and scope of study. Chapter 2 presents the literature review, which discusses the theoretical foundations such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2). It also discusses the relevant variables and develops the conceptual framework. All the discussion of the chapter is based on the prior research related to AI-driven tools in various sectors, especially focusing on the financial industry. Chapter 3 outlines the research methodology, involving sampling techniques, data collection methods, and data analysis techniques that were applied in the present study. Chapter 4 presents the results of demographic, awareness of the respondents related to AI investment tools, reliability test, descriptive analyses, diagnostic test and inferential analyses. It also included the discussion of the relationship between constructs in the research framework. Finally, a summary of the overall findings, managerial implications, limitations of the study and recommendations for future research.

1.9 Conclusion

In conclusion, this chapter has provided a background of artificial intelligence in the global and Malaysian financial sectors. This discussion highlights how the AI-enabled investment tools are shaping financial decision-making, especially through platforms or AI tools such as robo-advisors. While Malaysia is still in the early stages of AI adoption and faces several challenges like legal framework uncertainties, a shortage of talent, and public concern that might influence the intended use of AI in investment among Malaysian investors. While the younger generations who have grown up with digital technologies might also have concerns when using the AI tools. Recognising these gaps, the current study focuses on the young investor, specifically UTAR students, as a key demographic whose adoption behaviours will shape the future trajectory of AI in the finance industry. By applying a hybrid TAM–UTAUT2 framework extended with demographic variables, this research seeks to identify the factors influencing their behavioural intention to adopt AI-enabled investment tools. The result gained will not only contribute to academic understanding but also guide the fintech services providers or policymakers in designing more effective strategies or AI integration products and services in Malaysia.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

2.1.1 Fintech and AI

In recent years, financial technology (FinTech) has received significant attention from research communities. The term FinTech is a combination of information and financial technology. FinTech, or the introduction of new technologies into the financial sector, is now transforming the financial industry (Goldstein et al., 2019). It incorporates more efficient IT technology, convenience, affordability, flexibility and offering individualised service. This improvement is driven by advanced technologies like cloud computing, big data, blockchain, artificial intelligence, etc., which can produce new business models, technological applications, and product services. These technologies can also change the financial market and the way financial services are delivered, ultimately increasing the traditional financial industry's efficiency and lowering operating costs. Therefore, financial services have undergone a significant transformation as transactions become more convenient, safe, and affordable (Lv & Xiong, 2021).

Among these fast-growing technologies, artificial intelligence (AI) has become an industry leader by transforming data-driven innovations and decision-making capacities in a variety of industries. Similarly, Yangqing Duan, John S. Edwards and Yogesh K Dwivedi (2019) discuss that artificial intelligence (AI) is the capacity of a computer to learn from the past, adjust to new inputs, and then accomplish tasks that are similar to those performed by humans. Rather than a single technology, AI is a group of technologies. Meaning to say, it involves several well-known foundational fields like virtual assistants, robotic process automation, computer vision, natural language processing, and advanced machine learning (Yahya Khalifa AL-

HAJI & Suzaida Bte. BAKAR, 2024). These advanced technologies of AI have led to the daily tasks that were previously carried out by humans being taken over. AI is advancing quickly in some fields, including predictive analytics (Bokonda et al., 2020; Lorenzo et al., 2018), augmented and virtual reality (Federica Murmura et al., 2024; Al-Ansi et al., 2023; Pereira et al., 2023b), natural language processing (NLP) (Olujimi & Ade-Ibijola, 2023), generative AI (Mannuru et al., 2023; Sætra, 2023), and AI-enabled robotics (Soori et al., 2023). Referring to Rodrigues et al. (2022) and Noreen et al. (2023), AI has been used in a variety of industries, such as government payments, healthcare, online commerce, logistics, and finance, among others.

For illustration, in the banking industry, AI can assist banks in managing their financial services and interacting with clients while providing tailored goods (Doumpos et al., 2022). Jagdish N. Sheth, Varsha Jain, Gourav Roy and Amrita Chakraborty (2022) also found that although AI has become a key element of personalised banking, expansion in emerging nations is not guaranteed. The foundation of artificial intelligence (AI) is the computing of intricate mathematical algorithms that, under specific logical conditions, communicate quickly through computer systems (Noreen et al., 2023). According to Patel et al. (2022) and Noreen et al. (2023), Various financial computational activities in banking operations can be completed more quickly and efficiently using AI-based digital financial services than with conventional approaches. According to Shmuratko and Sheludko. (2019) and AL-Dosari et al. (2022), AI-driven solutions enable banks to provide multichannel customer access, learn about customer preferences, and customise services to meet the demands of their clients. Other than that, the NLP, a key AI technique used in chatbots (Shubham Chaurasia et al., 2023), robo-advisors (Nurillo Ablazov et al., 2024), and voice assistants (Fungai Jacqueline Kiwa et al., 2024; Mohapatra et al., 2025), is becoming broadly accepted by consumers across a range of service industries. The banking sector is frequently considered to be one of the most important service industries because it serves a diverse customer base with a range of backgrounds who use the same services. Since chatbots and robo-advisors have made customer engagement services more accessible, time-saving, and easy, AI in banking has drawn more clients to engage in banking activities and make more investments (Yi et al., 2023). This further boosts the utilisation of AI in the finance field in order to gain a higher profit and save costs.

2.1.2 AI in investment

In the financial sector, artificial intelligence (AI) has emerged as a significant innovation, particularly in asset management, where it improves decision-making, risk assessment, and process execution (Sandia Alfzari et al., 2025). Artificial intelligence has been widely used in risk management, financing and investment decision-making, and service enhancement. It has also changed the financial industry's value chain and had a major impact on the financial market's compliance regulation and enhancing its efficacy (Qian et al., 2024).

One of the main areas where AI has made a huge impact in investing is in data-driven investment strategies. With the growth of data sources and the development of big data analytics, investors now have access to a wealth of information that may guide their decisions and produce better results (Ojonugwa et al., 2024). AI-powered algorithms are able to analyse this data in real time, spot trends and patterns, and produce useful information that can guide investment plans. Also, based on the studies from Dwivedi et al (2021), it has been interpreted that the feature of the AI, which is able to process massive volumes of real-time data, contributes to more accurate estimations. Consequently, it helps the asset managers make timely and effective judgments (Sandia Alfzari et al., 2025).

Besides, AI can also provide a precise assessment, enabling investors to the investor can measure the social and environmental effects of their investment in a clear and quantifiable way. By using natural language processing (NLP) and sentiment analysis, it can sift through large volumes of textual data to glean insights on the social impact of investments, such as job creation, community development. When using the AI application, investors must create ethical standards and frameworks for proper use to ensure that investments have a positive social impact and adhere to moral norms. With this level of detail and accuracy in measuring impact, investors can track their progress toward goals, identify the areas for improvement, as well as maximise the overall effectiveness of their investment strategies (Ojonugwa et al., 2024).

Additionally, applying AI in asset management helps with fraud detection, regulatory challenges and boosting efficiency. This field of study is useful for machine learning algorithms because they may identify potential irregularities in transaction patterns that might indicate fraud in the security frameworks of financial organisations (Farahani & Esfahani, 2022). This preventive approach to risk management is considered useful and smart, particularly in the modern world, where financial offences are becoming more sophisticated. Moreover, AI lowers operational risks by automatically completing tasks associated with new or modified financial rules, improving compliance with mandatory reporting (Anagnostopoulos, 2018).

2.1.3 Machine Learning in Finance

In AI, machine learning (ML) has machine learning (ML) risen in popularity in various industries, and the most affected field is the finance industry. AI and ML are widely used in finance because they can process massive amounts of data, spot trends that are hidden from view, and make faster decisions compared to conventional techniques (Muhammad et al., 2022). According to Khanna & Jha (2024), Machine learning (ML) and deep learning (DL) are broadly used to find previously unidentified patterns of illegal financial behaviour utilising vast volumes of data. As an example, ML and DL are useful in stock trading, portfolio management, default risk and credit (Han & Yang, 2018; Muhammad et al., 2022), and money laundering detection (Jullum et al., 2020).

Recent research highlights that machine learning can enhance investment decision-making by consistently outperforming traditional passive strategies. According to Parisi and Manaog (2024), it has been proven that the ML algorithm is more accurate and interpretable, providing faster and more reliable decision-making for investors. Therefore, it can help the investor to improve their portfolio management and enhance long-term financial planning. On top of that, past research from Grudniewicz & Ślepaczuk (2023) found that machine learning-based tactics performed better than the conventional buy-and-hold strategy. Even though there is no best model in every market, Bayesian Generalised Linear Models (BGLM) and Linear Support Vector Machines (SVM) demonstrated the most resilience across a variety of markets and circumstances. This demonstrates how machine learning assists investors in identifying trends, modifying their approaches to suit various contexts, and ultimately coming to more profitable and well-informed investing selections.

Moreover, a study in the Brazilian market demonstrated that machine learning models can assist new investors by using the fundamental indicators to identify stocks as 'good' or 'bad' investments. Among the tested models, the Decision Tree achieved the highest accuracy (77%) and offered the best balance between identifying profitable and unprofitable investments, reducing the risk of poor investment choices. This research further highlights that machine learning in AI can serve as a valuable decision support tool for assisting investors in minimising risk and making more informed investment strategies (Oliveira et al., 2022). Chen-Hong Yang, Tshimologo Molefyane, Borcy Lee, Ting-Jen Hsueh and Yu-da Lin (2025) have tested the accuracy of the machine learning forecasting capabilities by using a machine learning model, such as the Gated Recurrent Unit (GRU). This prior research has shown that the GRU achieved the lowest forecasting errors among competing models, with MAE of 0.743, RMSE of 0.963, and MAPE of 67.936%, significantly outperforming traditional models such as ARIMA. This means that the advanced machine learning models can provide more accurate investment forecasts, helping investors and policymakers make better-informed decisions. Nonetheless, the study from Kell et al. (2021) also showed that the online machine learning algorithm is more accurate when compared to offline machine learning algorithms, with an MAE is 30%.

Furthermore, Asere and Nuga (2024) said that AI and ML can greatly improve the prediction of market trends and help the investor make efficient decisions to manage their portfolio. This is due to this study has found that machine learning can AI and machine learning can possess massive datasets to uncover hidden patterns and automate trading to guarantee that the risk is effectively managed compared to the traditional method. Prior research from Arroyo et al. (2019) shows that machine learning can effectively predict startup outcomes using company, funding, and founder data. The Gradient Tree Boosting (GTB) model achieved the highest accuracy (82.2%) and was especially strong in forecasting additional funding rounds (around 68% precision). Random Forest and Extra Random Trees were particularly effective in identifying high-reward outcomes like acquisitions and IPOs, performing over ten times better than chance. These results highlight ML's potential as a valuable tool for venture capitalists to reduce risk and improve investment decisions.

2.1.4 Robo Advisor in Asset Management

The first robo-advisor created by Wealthfront and Betterment provides individualised service with little to no human involvement (Zhang et al. 2021). According to Luo et al. (2024), due to the growing acceptance and popularity of robo-advisors, financial institutions have made large investments in them. Robo-advisors are computer programs that provide investors with online financial advice with little to no human involvement (Eren, 2023). However, Tertilt and Scholz (2018) said that a robo-advisor is a software that is data-driven and utilises specific algorithms. These algorithms operate by analysing information gained from investors through a series of questions. This activity can also be defined as risk profiling. Risk profiling can be improved through the successful application of AI (Artificial Intelligence), social media analysis, psychometrics, and big data techniques. Since robo-advisors can give investment suggestions based on an investor's profile, it can be used for many goals, like saving for education, buying a home, planning for retirement, getting protection, or even managing inheritance (Fahruri et al., 2025). In general, a robo-advisor service uses five main dynamics to function, which are asset identification, investor risk profile establishment, portfolio optimisation, tracking and rebalancing, and performance reporting (Dong et al. 2021).

One of the key advantages of robo-advisors is their speed and convenience, with customers often able to enrol and invest within 10 minutes (Belanche, Casalo, & Flavian, 2019). This efficiency is made possible because robo-advisors offer more individualised and flexible investing solutions by using big data analytics and sophisticated machine learning. Machine learning algorithms behind robo-advisors examine huge amounts of data for both historical and current, and spot patterns and trends that help them create more individualised and precise investment plans (Syed & Kavitha Reddy Janamolla, 2024). This idea is further supported by Tokic (2018), who demonstrated that a decision can be made automatically by a robo-advisor based on shifting market conditions. In contrast to the conventional approach of getting investment guidance from human advisers, financial robo-advisors use algorithms to rapidly evaluate data and create asset portfolios to give personalised investment advice (Hong et al., 2023).

Also, investors' cognitive biases can be eliminated by automated investment systems such as robo-advisors when making investment decisions (Bhatia et al., 2022; Jung et al., 2018; Ahmad et al., 2025). Therefore, applying robo-advisors can help to reduce and manage investors' self-control concerns because investor often allow their emotions to affect their decisions, which might lead to irrational investing choices. These advisors help to overcome judgment bias and minimise human errors, which improves the investment accuracy of the investors (Jung et al., 2018).

Similarly, Ahmad et al. (2025) also indicate how robo-advisors can reflect on the bias to make a good investment decision. In this research, it was found that robo-advisors can mitigate the effects of availability and loss aversion biases, while amplifying price anchoring and representativeness biases. This means robo-advisors can guide investors to prevent some mistakes, but it cannot remove all biases. However, the research that focuses on India discovered that robo-advisors are not yet advanced enough to carry out accurate risk analysis and profiling, which reduces their effectiveness in addressing investor biases. Meaning to say, while robo-advisors have strong potential to help minimize such biases, they still face major challenges, especially in creating more reliable profiling systems before they can fully deliver on this role (Bhatia et al., 2020).

On the other hand, several studies also prove that the utilization of the robo-advisors can help to save costs. For instance, Uhl and Rohner (2018) found that robo-advisors might save about 4.4% of fees annually compared to traditional fianncial managers. Robo-advisor technology also allows investors to access more user-friendly and less costly digital services compared to person-to-person services (Fatima & Chakraborty, 2024). Ahmad et al. (2025) have also demonstrated that robo-advisors are more cost-effective and time-saving, as they are accessible 24/7 and can accelerate decision-making by offering instant suggestions. Leow et al (2021) implied that robo-advisors enabled small investors to access automated asset management with lower investment barriers and minimal fees and reduce potential conflicts of interest. More specifically, investors who are concerned about their costs will be more inclined to employ low-cost financial services (e.g. robo-advisors), reducing the need of costly financial advice, such as human financial counsel. (Brenner & Meyll, 2020).

Another significant advantage of AI-driven robo-advisors is their capacity to keep learning and improving. AI-enabled platforms can improve the accuracy and efficacy of their investment suggestions by gradually improving their algorithms through the use of feedback loops and reinforcement learning techniques (D'Acunto et al., 2019). Because of this ongoing learning process, AI-powered robo advisors are able to keep ahead of market trends and adjust to the shifting financial landscape. Robo-advisors powered by AI can incorporate with other data sources, such as geopolitical events and social media sentiment, into their decision-making processes (Syed & Kavitha Reddy Janamolla, 2024).

In a nutshell, the benefits of utilising a robo-advisor have encouraged investors to shift from traditional to AI-driven tools, ensuring their profits from a well-managed portfolio.

2.1.5 Young Investor

Young Retailer Investors (YRIs) are one of the retail investor groups that have less algorithmic aversion and a greater propensity to employ FRAs than their older colleagues (Brenner & Meyll, 2020; Rossi & Utkus, 2020). This can further be proven by Fischet al. (2018) and Lopezet al. (2015), who said that younger investors (i.e., 'Millennials') are more likely to seek robo-advice because they often hold more exchange-traded funds (ETFs) and have small portfolio value. Brenner & Meyll, 2020) also demonstrated that the investor was split into two groups, which are the only robo-users' group and the only human advisor users' group. Then, its findings discovered that the robo-users' group is built by the younger investor, whereas the only human advisor users' group tends to be the oldest investor. This result indicates that the younger investors are more open to using AI-based financial tools like robo-advisors compared to older investors who strongly prefer traditional human advisors. Additionally, Fecht et al. (2018) found that younger investors are basically high-technological people but have little experience in personal finance, thereby having a favourable attitude towards the innovative and app-based financial solutions over conventional services. These phenomena occur because the younger investors, who have a lower income and a small amount of investment, are always disregarded by the traditional financial advisors.

Some rather anecdotal evidence, such as Tokic (2020) reported that younger investors often invest in well-known equities like Tesla or Apple, indicating that they are actively and positively engaged with these innovative investment platforms. According to the 2017 Global Findex survey, only 18% of young generations in the world use financial institutions to save their money (Demirgüç-Kunt et al., 2018). Findings from Fatima and Chakraborty (2024b) implied that anxiety does not significantly affect the behaviour intention of young investors to use the robo-advisor since they are not too worried about privacy or security issues when using digital tools compared to older investors. This result means the young generation prefers to adopt AI when trading rather than older investors. Hence, Younger investors have recently been targeted by the emergence of (social) trading platforms like Robinhood and trader user groups. These platforms generate a significant interest in the investment habits and performance of younger investors (Harms, 2021).

2.2 Theoretical Development

2.2.1 Technology Acceptance Model (TAM)

In the early stages of technology acceptance research, the default rate of information technology applications was very high, with major software companies suffering substantial financial losses from systems that users rejected. (Davis 2015). Davis, a business engineer, was one of the first to deal with the topic that explore how users respond to digital technologies ("computer-based information systems", Davis, 1986, p. 7). He aimed to find out how system design characteristics influence user motivation, which led to the development of the Technology Acceptance Model (TAM). This model is now frequently used to forecast how well users will embrace new technology (Alwakid et al., 2025). For example, TAM has been employed in some of the past research, including online payment or services, cryptocurrencies, AI-based reviews (Cruz-Benito et al., 2019), student quality assessments (Tam, 2014), and digital technologies in education (Scherer et al., 2018; Roy et al., 2022).

In order to assess digital technologies both before and during deployment, developers of new hardware and software could utilise the Technology Acceptance Model as a theoretical foundation for actual user acceptance testing (Davis, 2015). According to Lou & Li (2017), TAM is useful for predicting and describing the technological behavior of clients. It is founded on the principle of reasoned action (TRA), a psychological theory that explains accepting behavior (Manrai & Gupta, 2022). Fred Davis also found that there were two dominant reasons why people chose to reject a new system after interviewing with end-users. These two key beliefs are perceived usefulness and perceived ease of use(Scherer et al., 2018).

Perceived Usefulness (PU) can be defined as “the perception of how well a new technology is expected to improve performance efficiency and usability”. While perceived ease of use (PEOU) refers to the “perception that the latest technology is effortless” (Davis, 1989; Roy et al., 2018). According to David (2015), these two beliefs shape the user’s attitude, which then leads to a behavioural intention. These four variables collectively serve as the foundation for TAM, which explains “how users are motivated to use the system (Fig. 1; Davis, 1986, p. 11; Schorr, 2023). In simple terms, the negative or positive attitude towards technology in TAM is explained by PEOU and PU (Nguyen et al., 2025), and then ultimately reflects the behavioural intention to adopt the technology. Besides, TAM emphasises the significance of perceived usefulness and ease of use, two concepts that have been shown to account for more than 40% of the variation in user intentions (Legris et al., 2002).

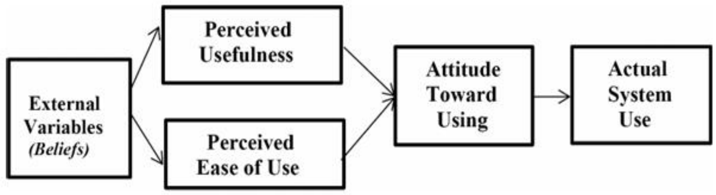


Figure 5: First version of the Technology Acceptance Model (Davis,1986)

Due to its robustness, the Technology Acceptance Model (TAM) has been widely applied across industries to explain users' behavioural intentions to adopt new technologies. For example, in the education sector, TAM has been used to predict students' intention of AI chatbots (Alwakid et al., 2025) and AI-based robots (Roy et al., 2022). In financial technology, several studies have employed TAM to examine factors influencing the adoption of robo-advisors (Singh & Kumar, 2024), cryptocurrency (Almajali et al., 2022; Nguyen et al., 2025), AI (AlAmayreh et al., 2023b), and digital payment services. Similarly, in the banking sector, TAM has been integrated with other models to investigate technology adoption in online and mobile banking (Tiwari, 2020). More recently, TAM and its extensions have been applied to examine how Jordanian SMEs adopt web-based social networks (WBSNs) as part of their marketing strategies (Alkhasoneh et al., 2025). These empirical findings demonstrate TAM's flexibility and predictive power across diverse contexts, reinforcing its relevance as a theoretical foundation for examining technology adoption.

Nonetheless, some scholars have identified several limitations of the TAM. Firstly, Davis (1993) pointed out that relying on self-reported usage of TAM can introduce bias when studying technology adoption. While Fishbein and Ajzen (1975) and Davis et al. (1989) also noted that TAM can be difficult to apply in empirical research. Another limitation is that TAM does not have complete measurements, especially in studies that focus on user intention, attitudes or perspective rather than actual usage behaviour (Mathieson, 1991). In addition, the original TAM concentrated on individual use of technology and did not take social influences into consideration (Yahya Khalifa AL-HAJI, & Suzaida Bte. BAKAR., 2024).

Meanwhile, TAM does not account for potential other factors that could significantly affect intention to use a technology, such as availability of resources (Almajali et al., 2022b). Referring to Tiwari. (2020), it shows that TAM's basic constructs do not accurately represent the variety of user work contexts and ought to be expanded and enhanced. Because TAM ignores intrinsic motivations, its use in a consumer setting where information technology is accepted. It is also used not only to accomplish tasks but also to satisfy emotional needs may be restricted (Taherdoost, 2018). To overcome these limitations, extensions such as UTAUT2 have incorporated additional constructs such as social influence, facilitating conditions, price, habit, and hedonic motivation. These extra elements make the framework more complete and better suited for explaining how people accept technology in today's environment.

2.2.2 UTAUT2

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been used in a variety of contexts to investigate technology acceptance at the personal level and usage intention. Studies have consistently validated the UTAUT model's resilience and efficacy (Donmez-Turan, 2019; Pynoo et al., 2011). Despite this, a growing amount of research suggests that the UTAUT model may not be sufficient to forecast people's IT adoption behaviour because it was created in an organisational context (Du & Liang, 2024). Plus, the UTAUT model had to be extended to the consumer context due to the growth of consumer technologies, which focused on the hedonic value (intrinsic motivation) of technology users.

UTAUT2 is a comprehensive theoretical framework used by researchers to forecast and determine technology acceptance and usage behavior. Performance expectancy, effort expectancy, social influence, and facilitating conditions are the four main constructs that make up this expansion of the original UTAUT paradigm (Ashrafi, 2023). In 2012, Hedonic Motivation, Price Value, and Habit serve as further variables in the most recent model (UTAUT2) (Tamilmani et al., 2021). Taking into account elements including perceived utility, usability, societal pressures, and personal preferences, these constructs work together to forecast consumers' intents and behaviors with regard to adopting technology (Marak et al., 2025). Therefore, UTAUT2, a more complex version, was created to predict technology utilisation and user willingness more consistently (Bernice et al., 2024).

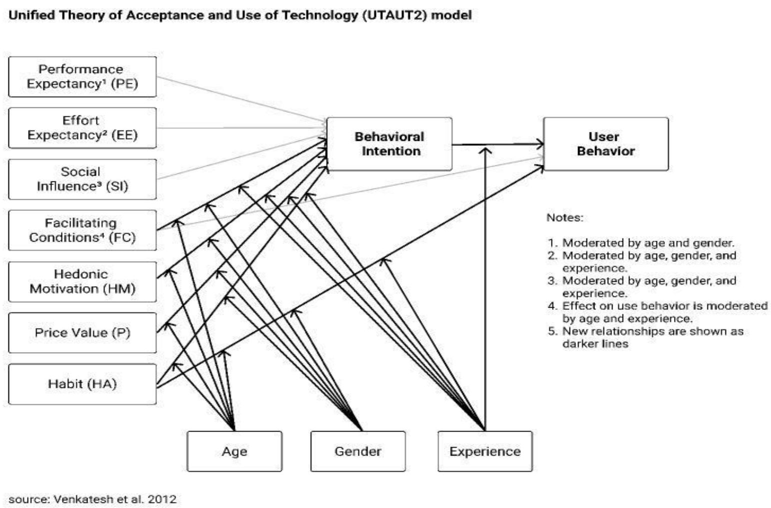


Figure 6: Version of UTAUT 2 (Venkatesh et al. 2012)

This model has now been widely validated for users' intention to accept. For illustration, it has been applied to a variety of technological kinds, from as general as mobile internet (Patricio Esteban Ramírez-Correa et al., 2014), the utilisation of robo-advisors, digital education (Ahmad et al. (2025) , and digital business. (Ye et al., 2025). Some of the empirical findings demonstrate that UTAUT2 is a strong framework for interpreting technology adoption across various sectors. In China, research on digital intangible cultural heritage found that no single factor alone could explain adoption; instead, combinations of hedonic motivation, social influence, performance expectancy, and immersion worked together to encourage users' willingness to engage with digital cultural experiences (Ye et al., 2025). In a different context, a study of SMEs in Jordan showed that performance expectancy, effort expectancy, and social influence were key drivers for adopting web-based social networks, which in turn improved brand awareness, sales growth, and customer engagement (Alkhasoneh et al., 2025b).

Broader reviews also highlight that across fields such as business, education, health, and media, performance expectancy and effort expectancy remain consistent predictors of adoption, while the influence of social factors is stronger when use is mandatory and tends to weaken with experience. Additionally, facilitating conditions are quite significant for senior users (Schorr, 2023). In the finance industry, previous studies using UTAUT 2 have shown that performance expectancy, effort expectancy, social influence, habit, price value, and facilitating factors all have a substantial impact on users' inclination to use fintech services (Amnas, Selvam, & Raja, 2023). Taken together, these studies illustrate how UTAUT2 captures both the psychological drivers and the contextual influences that shape technology acceptance.

This rise in using this framework among scholars to explore diverse sectors of digital tools willingness is because of its thoroughness and systematic nature (Ye et al., 2025). Compared to UTAUT, which is primarily designed for an organisational context, UTAUT2 is based on the individual’s viewpoint. It examines the factors that influence a user’s intention to adopt new technologies (Abrar et al., 2019). Moreover, the predictive ability of UTAUT2 theory is much higher in comparison to UTAUT, explaining about 74% of the variation in users’ behavioural intention and 52% of the variation in their actual use of the technology (Venkatesh et al., 2016). Furthermore, UTAUT2's incorporation of hedonic motivation aids in accounting for the subjective and affective components of consumers' decision-making when utilising financial robo-advisory services. This is particularly important when it comes to financial robo-advisory services because clients prefer to utilise them for both practical reasons and the satisfaction of reaching their financial objectives (Ashrafi, 2023).

2.3 Behavioral Intention (BI)

Behavioral intention (BI) is generally defined as "the degree to which a person has formulated conscious plans to perform or not perform some specific future behavior" (Warshaw & Davis, 1985). Simplify, the attitude a person has when carrying out a particular action influences how they behave. This explanation aligns with Fishbein and Ajzen (1975), who said that behavioural intention is means"a person's subjective probability that he [or she] will perform some behaviour". In the finance industry, the behavioral intention can be understood as the degree to which someone is intended, or ready to embrace and use a specific technology (Venkatesh et al., 2012; Du et al., 2025), such as AI, digital payments, and robo-advisors.

According to Ajzen (1991), intention is the primary factor influencing behavior when actual behaviour cannot yet be measured. This is because people are more likely to participate in usage behaviors when they display behavioral intentions (BI) when utilizing cutting-edge technologies (Drasch, 2019). As a result, behavioral intents can forecast future customer behavior sensibly and reliably (Dean & Suhartanto, 2019). This can be further proven by the prior studies, such as (Dixit et al., 2025; Du et al., 2025; Ammenwerth, 2019; Chatterjee & Bhattacharjee, 2020) show that the intention behaviour is positively affects the adoption behaviour. This suggests that understanding the intention is crucial to capture how different factors can influence the AI adoption behavior (Papathomas et al., 2025). Given that behavioral intention (BI) is a reliable indicator of carrying out the actions that embody that purpose (Zhang and Guterrez 2007), it will be used to test the willingness of university students from UTAR to adopt AI for their investment strategies in this study.

Previous research has tried to explain the behavioural intention to use the AI tools by various variables. Perceived usefulness and perceived ease of use are commonly used variables by scholars to examine the intention of the user to adopt the AI tools (Hu et al., 2025; Alwakid et al., 2025; Roy et al., 2022; AlAmayreh et al., 2023). Furthermore, the studies of Seiler and Fanenbruck (2021) had explained the behavioral intention to use digital investment solutions in the form of Robo Advisors by categorising these factors into several dimensions, including platforms, e-commerce, technology, and two control variables. Meanwhile, Khan et al. (2020) assessed the desire to utilize electronic stock trading using TAM theory and included a risk analysis of stock transactions (including the risk of opportunity cost, social, privacy, monetary, performance, and time). Besides, Tiwari. (2020) also explains the behavioural intention to adopt M-banking with the TAM model by extending other factors such as perceived risk, perceived trust, and perceived financial cost. To ensure the accuracy of the intention variance, the variable from UTAUT2 will be tested to explain the behavioural intention, especially the facilitating condition, which can positively influence the investor's intention to use the technology like a robo advisor (Roh, T., & Xiao, S., 2023) and AI tools for their investment strategies.

2.4 Hypothesis Development

2.4.1 Perceived Usefulness (PU)

According to Jogiyanto Hartono (2008), perceived usefulness (PU) refers to how people believe a system will help them perform better. It is also linked to a system's dependability in fulfilling user requirements. Within the Technology Acceptance Model, this variable has been shown to influence intention both directly and indirectly (Davis et al., 1989). Furthermore, Rogers (2003) considered perceived usefulness as a comparative benefit in the diffusion of innovation theory (DOI theory), illustrating the superiority of new technology over earlier technologies. Thus, in studies of new technology adoption, perceived usefulness has continuously been one of the most studied elements (Almajali et al., 2022), particularly in relation to new investment technology intention (AlAmayreh et al., 2023). This is because customers who are interested in trading or investing through new technologies are inclined to consider financial advantages they could gain when deciding on adoption, such as lower investment costs, 24/7 client service, and other benefits (Amayreh et al., 2023).

A previous study discovered that people tend to have a positive attitude when they think that robo-advisors are cost-effective, efficient and available instead of conventional services (Singh & Kumar, 2024). For instance, RAS-driven Fintech services provide users benefits including accurate portfolio management and safe, profitable guidance. The advantages that RAS provides, especially in personal banking and features like 24/7 customer support, reinforces the idea that the PU will have a direct impact on consumers' attitudes (Liu et al., 2023). Likewise, a positive attitude toward adopting new technologies, such as robo-advisors, can also be boosted by some beneficial functions that could be provided to fintech service users, including transparent profit data disclosure, portfolio reorganisation based on time and situation, and low fees (Roh et al., 2023). Similarly, Nainggolan and Handayani (2023) found that perceived usefulness (PU) significantly influenced attitude (ATT) toward using online capital market investment platforms in Indonesia, but it did not directly affect behavioral intention. This suggests that while users recognise the usefulness of the platforms, their intention to use them is shaped more strongly by the positive attitudes formed through this perception.

Additionally, Pusposari et al. (2024) found that perceived usefulness (PU) indirectly influenced students' intention to use AI-based mobile investment apps through attitude (ATT). While PU had a significant direct effect on behavioral intention, it also shaped a positive attitude, which further mediated its influence on intention. This highlights the dual role of usefulness in both shaping favorable attitudes and driving intention. Consistent with these findings, Belanche, Casaló, and Flavián (2019) demonstrated that perceived usefulness (PU) significantly and positively influenced attitude (ATT) toward adopting robo-advisors in the FinTech sector. This finding suggests that when users recognized robo-advisors as beneficial tools for managing investments, they developed more favourable attitudes toward their adoption. By referring to earlier studies, the following hypothesis was developed:

Hypothesis 1: Perceived Usefulness can influence the attitude toward AI-enabled tools for investment

2.4.2 Perceived Ease of Use (PEOU)

Perceived ease of use “the degree to which a person believes that using a particular system would be free of effort” Davis, 1989, p. 320), both psychologically and physically (Park et al., 2013). According to the TAM used to support the other models, perceived ease of use is regarded as a substantial and effective predictor of Attitude (ATT) in the technology adoption research (Lu et al. 2005). Since it has a positive impact on the intention through perceived attitude, this variable becomes one of the crucial determinants derived from the Technology Acceptance Model (Pusposari et al., 2024).

This relationship can be strongly supported by Roy et al. (2022), who implied that PEOU positively influences the ATT to adopt AI-based robots, meaning the individuals have the right attitude and understand that using these AI-based robots will be easier. Results on Almajali et al. (2022) confirmed a positive impact of perceived ease of use (PEOU) on users’ attitude toward adopting cryptocurrency, providing strong support for this relationship. Nainggolan and Handayani (2023) found that perceived ease of use (PEOU) had a significant positive effect on attitude (ATT) toward using online capital market investment platforms in Indonesia. This suggests that when financial technologies are perceived as easy to operate, users are more likely to develop favorable attitudes toward their adoption. Too, J. Park et al. (2024) found that perceived ease of use (PEOU) significantly enhanced consumers’ attitudes toward adopting AI avatar services, highlighting the role of usability in shaping positive perceptions of emerging technologies.

Similarly, Setiawan and Setyawati (2020) also found that attitude and convenience of use were positively correlated in their individual investigations. Still, Hong, Suh, & Kim (2009) demonstrated that users' attitudes and the perceived value of using systems are positively impacted by perceived ease of use. Along with users who found robo-advisors simple and convenient to operate, they expressed stronger favourable attitudes, reinforcing the role of ease of use as a key determinant of positive technology perceptions in financial decision-making (Belanche et al., 2019). These findings collectively suggest that for any new technology to be widely accepted, it must demonstrate ease of use, as this strongly shapes favorable attitudes and subsequent adoption (Almajali et al., 2022). Hence, the following relationship between perceived ease of use and attitude is established according to the previous result:

Hypothesis 2: Perceived Ease of Use significantly effect on the attitude toward AI-enabled tools for investment

2.4.3 Facilitating Condition (FC)

Facilitating Conditions (FC) are defined as “the degree to which an individual believes that organisational and technical infrastructures exist to support the use of a system” (Venkatesh et al., 2003). When consumers believe there is sufficient support and resources available to facilitate easy use, such as technical assistance, user-friendly interfaces, and training, they are typically more inclined to adopt new technologies (Venkatesh et al., 2003). During a new IT system is introduced in a highly competitive industrial setting, companies will coach staff members on how to keep a competitive edge (Pipitwanichakarn and Wongtada, 2021) and advertise the system to influence users' intentions and behavior (Geng et al., 2021).

Some studies have also demonstrated this positive relationship, such as Gan et al. (2021), which shows that using AI technologies without human interaction can improve the user experience by streamlining procedures, particularly during unique circumstances such as the COVID-19 pandemic. Furthermore, the findings that robo-advisors with a user-friendly interface can boost adoption and reinforce favourable customer services have been found by (Yeh et al., 2022). Plus, Roh et al. (2023) found that Facilitating Conditions (FC) had a significant positive effect on Attitude toward adopting AI-enabled robo-advisors by mediating the effects of perceived privacy and trust on Attitude. Meaning to say, the researcher demonstrates that when users perceive strong support and infrastructure, along with privacy and trust, they develop more favourable attitudes toward robo-advisors. In sum, it can be concluded that the facilitating conditions will positively affect the attitude towards new technology adoption, and the following hypothesis has been developed:

Hypothesis 3: Facilitating Condition has a significant effect on attitude toward AI-enabled tools for investment.

2.4.4 Social Influence (SI)

Social Influence (SI) is defined as "the degree to which an individual perceives that others believe they should use a new system" (Venkatesh et al., 2003). SI is another important element affecting the adoption of technology based on the UTAUT model (Yeh et al., 2022). Accordingly, this study defines SI as the degree to which an individual perceives that others believe they should use AI-enabled tools. In general, people are more likely to experiment with new technology if they believe that their friends, family, or other significant figures support their use. Previous studies support this relationship by showing a positive correlation between social influence and the desire to use robo-advisors (Yeh et al., 2022).

As an illustration, Aksoy et al. (2020) discovered that SI has a beneficial impact on people's opinions on sport wearables. At the same time, Chen and Kuan (2012) obtained similar results from their study on the acceptance of playing mobile online games. Other studies have also confirmed positive correlations between users' attitudes and willingness to adopt future technologies, like close-field communication and widespread computing, and social norms (Chung et al., 2017).

In the context of robo-advisors in China, Roh et al. (2023) found that Social Influence had a significant positive effect on Attitude toward adoption. Their results indicate that perceptions of important others (e.g., peers, family, financial advisors, and broader social norms) endorsing robo-advisors meaningfully enhance users' favourable evaluations of the technology, thereby strengthening pro-adoption attitudes in the Similarly, Yeh et al. (2022) reported that Social Influence significantly shaped Attitude toward robo-advisors in Taiwan. Their study further highlighted that this relationship was negatively moderated by the investment-to-income ratio, meaning the positive effect of SI on Attitude was stronger for users investing a smaller portion of their income. In the context of Fang et al. (2025) revealed that Social Influence (SI) had a significant positive effect on Attitude, which in turn strengthened Behavioral Intention. The mediation results ($\beta = 0.052$, $p = 0.017$) indicate that peer pressure and support from colleagues or important others foster more favourable attitudes toward AI adoption, thereby indirectly enhancing librarians' intention to use AI. In short, the following hypothesis related to the relationship between social influence and attitude was generated:

Hypothesis 4: Social influence has a significant effect on attitude toward AI-enabled tools for investment.

2.4.5 Price Value (P)

Price value is determined as "the belief that the amount paid for a technological tool is matched by the benefits received". If the perceived benefits outweigh the Price Value (P), this will positively influence Behavioral Intention (BI)(Venkatesh et al., 2012). This means that people will be inclined to plan to use technology is caused by the financial advantages exceed the expenses(Ain et al., 2016).

In the finance industry, the experience and new investor who thinks that robo-advisors will accept customers with smaller account amounts and provide a substantial cost advantage over traditional investment advisors, including lower fees, which may not be provided by traditional financial services (Bhatia, Chandani, Atiq, et al., 2021). The study also confirmed that price value significantly influenced desirability, showing that investors in the UAE are more inclined to adopt robo-advisors when they perceive the financial benefits and services provided to be worth the associated costs (Ahmed et al., 2024). Alzyoud et al. (2024) also reported that price value significantly influenced behavioral intention, suggesting that users' perception of receiving good value for money is a strong predictor of their willingness to invest in cryptocurrencies. Referring to earlier findings, the hypothesis has been developed below:

Hypothesis 5: Price Value has an impact on Behavioral Intention to AI-enabled tools for investment.

2.4.6 Habit (HA)

Venkatesh et al. (2012) assert that habit is shaped by prior experiences, which may frequently affect the desire to apply a new technology (Ajzen, 1991), meaning people will be more desire to employ the technology if they are familiar with it (Zhou et al., 2022). In other words, people who internalise habits may not consider, recognise, or assess the motivations behind their acts if they frequently perform the same actions (Mittal, 1988; Ouellette and Wood, 1998). Subsequent studies have demonstrated the influence of HA on BI in adopting new technologies

To illustrate, Zhafira et al. (2025) in their study found that Habit had a significant positive effect on both Behavioral Intention and Use Behavior. This indicates that when users are accustomed to using financial technologies, they are more likely to continue adopting and actively engaging with robo-advisor platforms. Papathomas et al. (2025) further confirmed that Habit significantly influenced Intention to Use (ItU) AI banking services. This shows that prior use patterns and established routines encourage continued AI adoption in the banking sector. Similarly, the study Dixit et al. (2025) found that Habit strongly and positively affected both Behavioral Intention (BI), highlighting that repeated use creates familiarity and reliance on AI-enabled recommendation systems in e-commerce. Accordingly, a direct connection between Habit and Behavioural Intention to utilize AI-enabled tools is presented as below hypothesis:

Hypothesis 6: Habit significantly effect on Behavioral Intention to AI-enabled tools for investment.

2.4.7 Hedonic Motivation (HM)

In the context of technology use, hedonic motivation (HM) is defined by Brown and Venkatesh (2005) as the pleasure or delight one gets from using technology, with an emphasis on users' intrinsic motivation. Generally, hedonistically driven user interaction encourages consumption that consumers find enjoyable and satisfying. (Madhu et al., 2022). According to prior research, HM can assist in reducing annoyance in digital interactions (Salimon et al., 2017), and the UTAUT model includes it as a crucial component of technology adoption (Venkatesh et al., 2012).

As Gawior et al. (2022) show how people's improved ability to participate in fun activities naturally encourages them to use mobile technology more and affects their adoption behavior. According to Siyal et al. (2020), people are more inclined to adopt technology if they anticipate that it will satisfy their hedonic demands, which adds an additional level of motivation beyond practical advantages. In addition to improving the user experience overall, this emotional appeal increases users' strong and constructive desire to incorporate technology into their daily life (Al-

Azawei & Alowayr, 2020). In a very similar context, Alzyoud et al. (2024) and Jegerson et al. (2023) discovered that the UAE consumer's behavioral intention of cryptocurrency investment was significantly predicted by hedonic motivation.

Ahmed et al. (2024) found that hedonic motivation had a significant positive effect on the behavioral intention of AI-based robo-advisors among UAE investors. This highlights that enjoyment and intrinsic satisfaction from using AI-driven investment tools are important motivators driving adoption. In banking services, the study of Marak et al. (2025) found that hedonic motivation significantly increased Behavioural Intention to use chatbots. Based on earlier findings, the hypothesis has been generated below:

Hypothesis 7: Hedonic Motivation had a significant influence on Behavioral Intention to AI-enabled tools for investment.

2.4.8 Attitude (ATT)

Attitude (ATT) can be defined as the extent to which an individual prefers or disapproves of any technology. ATT is thought of as a mental inclination to depend on a specific technology (Roy et al., 2022). This means that attitude is a combination of three main constructs: emotional, behavioural and cognitive. (Fishbein et al., 1975). Nonetheless, studies indicate that people react more strongly to the feelings aspect while paying less attention to the other elements. This makes it challenging to accurately measure how people think about new technologies. Despite all of these measuring flaws, attitude is still a significant factor in determining the adoption of technology (Manrai & Gupta, 2022).

This can be proven by both important theories from the literature of TAM and UTAUT, which imply that individuals' attitude toward technology is a significant predictor of their behavioural intention to adopt new technology. Davis (1989) in the theory of the Technology Acceptance Model

(TAM) said that a person's attitude toward utilising a system serves as a gauge of their behavioral intention (BI), meaning that when customers have a favourable attitude toward technology can boost their intention to use it (Ikhsan et al., 2024). Similarly, attitude is considered a distinct construct that might pose problems in terms of discriminant validity since the main variables in the original UTAUT model are attitudinal aspects. Additional evidence from (Chong et al., 2021) implies that attitudes can help to lower barriers to innovation and facilitate transactions, showing it is the primary determinant of behavioral intentions (i.e. “the degree to which a person has a favourable or unfavourable evaluation of the behavior in question”, Ajzen, 1991, p. 188). Additionally, Suki and Ramayah (2010) claim that attitude has long been recognised to affect intention.

In the present study, the adoption of new technologies would be facilitated by having a positive attitude toward AI-based investment. Singh and Kumar (2024) found that trust, usefulness, and risk shape users’ attitudes toward robo-advisors, which then significantly influence intention. Ling et al. (2024) found that positive attitudes drive intention to adopt mobile investment platforms in Malaysia. Likewise, Dang et al. (2024) and Chua et al. (2023) confirmed that investors’ positive attitudes significantly increased their intention to adopt AI-generated financial advice and recommendations, with the effect being even stronger among those with higher risk tolerance. Roh et al. (2023), integrating UTAUT and TRA in China, confirmed that positive attitudes toward robo-advisors significantly increased users’ intention to adopt them. Similar findings were reported by Manrai and Gupta (2023) in India, where attitude strongly predicted investors’ intention to use robo-advisors. At the same time, Pusposari et al. (2024) found that students with more positive attitudes toward fintech services were significantly more willing to use them. Collectively, these prior studies show a constructive relationship between attitude and behavioral intention

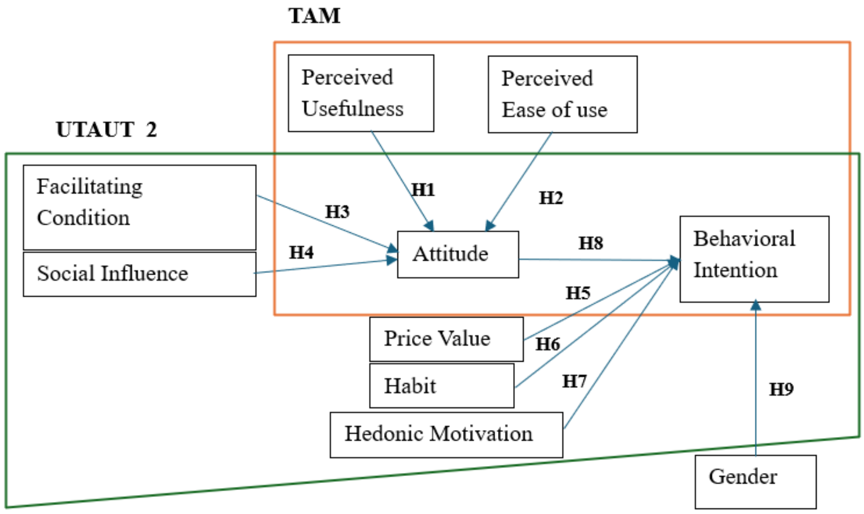
Hypothesis 8: Attitude has an impact on the behavioural intention of university students to use AI tools for investment.

2.7 Demographic Variable

It is also crucial to look at the set of consequences of the potential users' sociodemographic features in order to decide how best to connect the innovative, digitally intensive industry with its potential consumers (Méndez-Suárez et al., 2023), involving such as field of study, gender, and year level) (F. Wang et al., 2023). The existing research supports the idea that the acceptability of technology varies by gender. The majority of research contends that men view AI more favorably than women and that they are more socially desirable (e.g. Kuo et al., 2009; Schermerhorn et al., 2008). This can further be proven by Parlangeli et al. (2023), who said that women generally view robots as masculine objects, which is a particularly pertinent theory for the gender-sensitive design of humanoid robots. Terzis and Economides (2011) found that females had higher ratings for supportive environments, while males scored higher in the perceived usefulness of technology. Meanwhile, research from F. Wang et al. (2023) showed that male students reported higher self-efficacy, perceived usefulness, and stronger behavioral intentions to learn AI compared to female students. This highlights a gender gap, with men showing greater confidence and readiness to engage with AI. Therefore, the following hypotheses are generated:

Hypothesis 9: Male students are more likely than female students to demonstrate stronger behavioral intention to adopt AI tools.

2.5 Conceptual Framework



Source from: Designed for this study

In this study, the framework combines the theory of TAM and UTAUT2 to examine what is the factors that will influence the behavioural intention of the UTAR students. This combination is because of the limitations of the TAM. According to prior findings, the scholars had discovered some of the TAM's limitations, including self-reported usage bias (Davis, 1993), difficulties in empirical application (Fishbein & Ajzen, 1975; Davis et al., 1989), lack of actual usage measures (Mathieson, 1991), and exclusion of social influence (Yahya Khalifa AL-HAJI, & Suzaida Bte. BAKAR., 2024). Other than that, it also neglects contextual factors such as access to resources Almajali et al. (2022), and does not account for intrinsic or emotional motivations (Taherdoost, 2018).To address these weaknesses, extended models such as UTAUT2 add constructs like social influence, facilitating conditions, price value, habit, and hedonic motivation, making the framework more comprehensive explanation of the behavioural intention of adoption the new technology. Nainggolan and Handayani (2023) also proven that price value is not significant effect on BI.

On the other hand, two variables of UTAUT2 were not included in the framework of this study, which are effort expectancy and performance expectancy. The exclusion of these variables is due to some scholars have proven that they have the same idea as perceived usefulness and perceived ease of use. As an example, Vekenkatesh et 2003 have discussed that perceived ease of use and complexity as contained in other models carry the same concept of effort expectancy, while Performance Expectancy is interpreted as being equivalent and comparable in terms of perceived usefulness, expected results, and relative benefit. (Cox, 2012). Still, Iskender et al. (2022) has also said that effort expectancy and performance expectancy variables in UTAUT are similar to the perceived usefulness and ease of use of TAM. Then, according to Du et al. (2025) also mentions that the interpretation of the performance expectancy is closely related to the concept of perceived usefulness found in the Technology Acceptance Model, while the effort expectancy refers to the ease of use associated with technology.

Based on this evidence, the study adopts a hybrid framework by combining TAM and UTAUT2 while removing performance expectancy and effort expectancy. Therefore, the variables investigated in this study include perceived usefulness, perceived ease of use, and attitude from TAM, together with hedonic motivation, social influence, facilitating conditions, price value, and habit from UTAUT2. This integrated model not only eliminates redundancy but also captures both the technological perceptions and the broader social, motivational, and contextual factors influencing students' behavioral intention. The framework is also extended with demographic variables like gender, as it is less threatened as an independent variable by existing research. In summary, it can offer a deep and comprehensive understanding of the adoption of technology in the student context.

2.6 Research Gap

Over the years, some models have been widely applied to explain new technology adoption, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT2). Despite a large amount of prior research having been conducted on the topic of technology adoption, few of them has attempted to integrate the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2(UTAUT2) in examining behavioral intention towards adopting new technologies. Most of the existing studies rely on either TAM or UTAUT2 alone, which may inadequately capture overall users' perceptions as well as the overall motivational and contextual factors that may affect user adoptions. In addition, demographic variables such as age, gender, and education level—which significantly shape adoption behaviors—have been inadequately explored. Most prior studies distribute demographics as control variables or mediators. Meanwhile, only a few consider them as independent variables, and these often focus on gender, income, or education rather than academic stream. This creating a gap in understanding how a hybrid TAM–UTAUT2 framework, together with demographic considerations, to provide a more comprehensive explanation of technology adoption.

Another gap comes from the inconsistencies exist were found in prior findings regarding UTAUT2 constructs. A way an illustration, Yeh et al. (2022) as well as Chawla and Joshi (2020) demonstrated that Facilitating Conditions (FC) were found not to significantly influence attitudes toward robo-advisors in some studies, though they directly affected behavioral intention (Yeh et al., 2022), while other research reported FC had no direct impact on intention (Du et al., 2025; Romero-Charneco et al., 2024). Similarly, Singh and Kumar (2024) showed that Social Influence (SI) did not significantly shape attitude, contradicting prior findings. Interestingly, Habit (Ahmed et al., 2024; Du et al., 2025), Hedonic Motivation and Price Value were reported as non-significant in their effect on AI adoption in certain situations (Ashrafi, 2023; Bernice et al., 2024; Alkhasoneh et al., 2025; Amnas et al., 2023; De Blanes Sebastián et al., 2022). Other than that, if comparing to the earlier research, those scholars have implemented research on the intention to utilise AI in investment that is more focused on the investor or among citizens rather than students.

Accordance to the gap that has been identified, this study addresses these gaps by developing a hybrid TAM–UTAUT2 framework that excludes overlapping constructs and incorporates demographic variables. At the same time, this study also aims to carry out further testing of those variables that had mixed results found in earlier studies on UTAUT2 factors. In this way, it not only builds on existing theories but also provides a more complete and in-depth understanding of the factors that influence behavioural intention to adopt new technologies.

2.9 Conclusion

This chapter has reviewed the relevant literature on financial technology (Fintech), artificial intelligence (AI), machine learning, and robo-advisory services, with particular emphasis on their application in investment and asset management. Besides, the key theoretical models that are related to the technology adoption, namely the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), have been examined. Basically, TAM effectively explains technology adoption through perceived usefulness and perceived ease of use. However, prior studies found that it has limitations in capturing social motivational and contextual influences, which can be addressed by combining it with UTAUT2. Building on prior studies, this chapter conceptualised a hybrid framework that integrates TAM and UTAUT2 while excluding overlapping constructs such as performance expectancy and effort expectancy. At the same time, the inclusion of demographic variables as independent predictors has been proposed to address their underexplored role in shaping behavioural intention.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methods used to achieve the objectives of the study. It begins with the research paradigm that frames the investigation, followed by the design, sampling, data-collection procedures, and analysis techniques. By explaining these elements, the chapter shows how the study maintains consistency between its philosophical stance and the quantitative approach adopted to examine students' intention to use AI tools in investment strategies.

3.2 Research Paradigm

An American philosopher, Thomas Kuhn, originally used the term paradigm to refer to a philosophical approach to thought in his 1962 book. The word "paradigm" means "worldview" in educational research (Mackenzie & Knipe, 2006). This worldview is the viewpoint, or method of thinking, or school of thought, a collection of common beliefs that guides how research findings are interpreted or given meaning. Besides, as Lather (1986) clarifies that a research paradigm reflects the researcher's beliefs about the world they live in and wish to live in. It is made up of the abstract ideas and precepts that influence a researcher's perception, interpretation, and behavior in the world. According to Lincoln & Guba (1994), a paradigm is a fundamental set of ideas or a worldview that directs an investigation or research activity. To decide which research techniques to employ and how to analyze the data, the researcher examines the project's methodology via this conceptual lens. Paradigms are thus important because they offer ideas and guidelines that affect what should be studied, how it should be studied, and how the study's findings should be interpreted by academics in a given field (Kivunja & Kuyini, 2017).

Based on some reviews of earlier literature, there are 3 common types of research paradigms, which are positivism, interpretivism, and critical theory. Positivism assumes that reality exists apart from people. It is controlled by the unchangeable rules but not mediated by the human sense. Positivism's ontological stance on reality is that of realism, which holds that cause-and-effect linkages make the universe objective and predictable. The positivists' epistemological stance is objectivist in nature, with researchers acting as fair observers to examine phenomena that exist apart from them without altering what is being observed. Positivist methodology focuses on hypothesis testing and empirical evidence to analyze data and explain the link between independent and dependent variables (Rehman & Alharthi, 2016).

Moreover, Interpretivism is a "response to the over-dominance of positivism" (Grix, 2004, p. 82). Interpretive ontology opposes foundationalism. Meaning to say, it is to try to understand how people perceive the social phenomena they encounter, rather than to discover truth and knowledge that are universal, context-free, and valueless. Otherwise, Interpretive epistemology is subjective. It indicates that Observers cannot directly access the outside world without being tainted by their own worldviews, ideas, backgrounds, etc. Methodologically, Interpretive research uses qualitative techniques like document analysis, observations, and interviews to comprehend social events from the perceptions of those who take part (Cohen et al., 2017).

The Critical paradigm situates its research on social justice concerns and aims to address the political, social, and economic problems that can cause authority structures, conflict, social oppression, and struggle at any level (Kivunja & Kuyini, 2017). According to its historical realism ontology, gender, politics, culture, and religion all will influence reality. Epistemologically, critical theory is subjective since it assumes that no item can be studied without the researcher's influence. Methodologically, it is interactive and discussion based as it involves participants in a dialogue and in question design, data collection, and analysis to create awareness and bring about change (Lincoln & Guba, 1994).

Among these types of paradigms, the positivist research paradigm is most appropriate in this study. This can be attributed to its fundamental beliefs of determinism, empiricism, parsimony and generalisability (Cohen et al., 2000). This study aims to test the relationship between independent variables (perceived usefulness, perceived ease of use, habit, price, hedonic motivation, etc.) and the dependent variable (intention of students using AI tools in investment strategies) in order to predict these cause-and-effect relationships. This idea aligns with the concept of 'determinism' assumptions of the positivist, which assumes that observable phenomena are caused by recognizable causes. Concurrently, this research must gather the data in a quantitative way (e.g., using survey questions), has meets the empiricism assumption of the positivist paradigm that requires the gathering of verifiable, quantifiable information. Finally, focusing on UTAR students as the research population also satisfies the assumption of generalisability that demands the findings should apply beyond the specific sample (Kivunja & Kuyini, 2017).

3.3 Research Design

This research has used the quantitative design to analyse the factors affecting the behavioral intention of the students in adopting AI tools for their investment strategies. Quantitative research is the method that is typically associated with positivist or post-positivist perspectives, wherein researchers seek to "eliminate their biases, remain emotionally detached and uninvolved with their objects of study, and test or empirically justify their stated hypotheses" (Johnson & Onwuegbuzie, 2004, p. 14). In quantitative research, objects are measured and questions like "how long," "how many," and "the degree to which" are always asked. Accordingly, this study examines the degree to which students utilise AI-powered tools for investment management. Because the goal of the present study is to examine cause-and-effect relationships, quantitative methods are suitable for collecting, analysing, and interpreting measurable data to test the proposed hypotheses (Ghanad, 2023). This concept is aligned with Gall et al (2003), who said that positivist researchers can use the quantitative approach to solve research challenges and develop hypotheses, through closed-ended questionnaires, standardised tests, actual experiments or less comprehensive quasi-experiments

In this study, a cross-sectional survey design is used to gather information from the targeted sample (UTAR students) at one point in time (Arshad et al., 2024). Referring to Ghanad (2023), cross-sectional studies enabled researchers to evaluate various variables at once time. This is quite useful and valuable for the study that investigates a lot of independent variables as it can help them to save their time. The deductive method is also applied to guide the current research, meaning that the hypothesis was developed using the established theory (TAM and UTAUT2) and then proceeds to evaluate of theory's implications using data obtained (Mohammed, 2024; Arshad et al., 2024). At the same time, it was further extended by incorporating relevant demographic variables.

Additionally, the quantitative design emphasizes the objective rather than the subjective in order to evaluate the hypotheses and either validate or improve the theoretical links (Hassan, 2024). This is due to the hypothesis that can only be tested when numerical data is generated (Rehman & Alharthi, 2016). This characteristic of the quantitative design is similar to the assumption of empiricism of the positivist paradigm that requires collecting verifiable and numerical data to support the theoretical framework selected for the study and allow the researcher to test hypotheses developed (Kivunja & Kuyini, 2017). Therefore, this paper focuses on quantitative data using a closed-ended questionnaire in order to obtain numerical data to analyze the behavioral intention of UTAR students in using the AI tools for investment management.

3.4 Development of Research Framework and Hypothesis

Figure 3.1 shows the framework of this study, which has integrated the theory of TAM (PE, PEOU, ATT) and UTAUT2 (SI, FC, BT, P, HA and HM) to analyze the behavioral intention of students in adopting AI-enabled tools for their investment strategies. This framework is also extended with the demographic variables, which are gender and stream, to look at whether the different genders and academic knowledge will influence a student's intention to use a new technology.

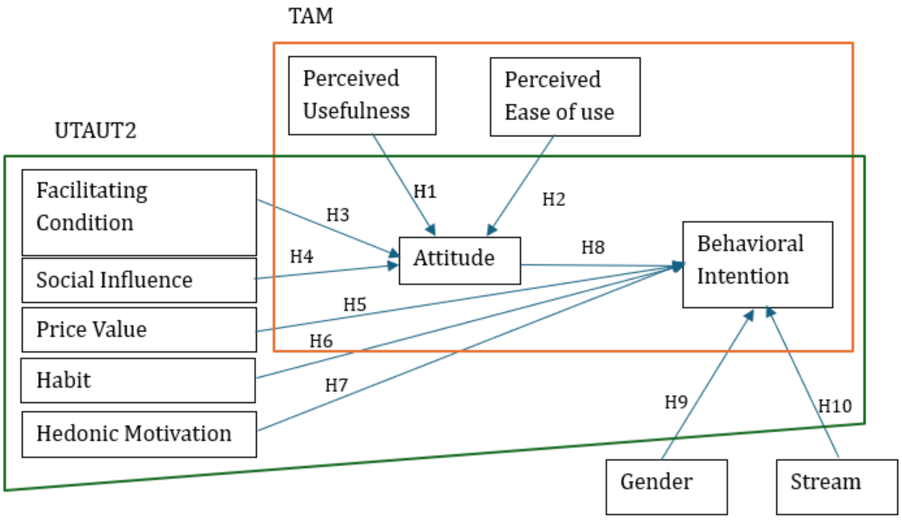


Figure 7: Conceptual framework of this study

Below are the multiple regression formulas that is represent the research framework for this study:

$$BI_i = \beta_0 + \beta_1 P_i + \beta_2 HA_i + \beta_3 HM_i + \beta_4 ATT_i + \beta_5 GNDR_i \qquad (3.1)$$

$$ATT_i = \beta_0 + \beta_1 PU_i + \beta_2 PEOU_i + \beta_3 SI_i + \beta_4 FC_i \qquad (3.2)$$

where:

BI= Behavioral Intention

ATT= Attitude

P= Price Value

HA= Habit

HM= Hedonic Motivation

GNDR= Gender

PU= Perceived Usefulness

PEOU= Perceived Ease of Use

SI= Social Influence

FC= Facilitating Condition

3.5 Data Collection Method

Primary data for this study will be collected through a structured online questionnaire designed to examine Universiti Tunku Abdul Rahman (UTAR) students' acceptance of AI tools in investment strategies. The survey will include closed-ended questions that measure perceived usefulness, perceived ease of use, attitude, facilitating conditions, social influence, habit, price value, hedonic motivation, demographic characteristics, and behavioral intention to adopt such tools. The survey will be conducted from September to November. To guarantee the consistency and ease of analysis, all the measurements of the items in the construct are using a five-point Likert scale (1=strongly disagree and 5=strongly agree)"(Alkhwaldietal.,2022).

The questionnaire link will be distributed through UTAR student email lists and social media platforms such as WhatsApp, Instagram, and Rednote. This method enables participation from students across the Kampar and Bandar Sungai Long campuses. Meanwhile, it is also distributed through the offline method. The purpose of this study, confidentiality and informed consent will all be covered on the first page (introduction page) of the questionnaire. Using the online approach is want to ensure broad reach, cost efficiency, and timely data collection within the project's schedule. Given that the current study explores AI, an online survey is the most effective and appropriate approach for researchers to gather and analyse data (Bin-Nashwan et al., 2023b, 2023c; Chau et al., 2025). On top of that, using the platforms or applications to distribute the questionnaire can help to mitigate the potential problem of non-response bias (Fang et al., 2025).

3.6 Sample

If the survey only focused on student respondents, then research findings would not be representative of the population (Bhattacherjee, 2012). In this study, the target sample is specifically the students of Universiti Tunku Abdul Rahman (UTAR), rather than the general Malaysian public or all young investors. Accordingly, the sample comprises current UTAR students from both the Kampar (Perak) and Bandar Sungai Long (Selangor) campuses, including those enrolled in Foundation, Undergraduate, Postgraduate, Master's, and Doctoral (PhD) programmes. Universiti Tunku Abdul Rahman, which was founded in 2002, is a private and non-profit university in Malaysia. Approximately 20,000 students are enrolled at this university (at the campuses in Sungai Long and Kampar). UTAR offers more than 120 academic programs, from the foundation to PhD levels, covering accounting, business and management, the arts, engineering, medicine and health sciences, and information and communication technology. This wide range of programmes has attracted international students from over 30 countries (Team, 2021).

3.6.1 Sampling Elements

The sampling elements for this study are the students who currently study at University Tunku Abdul Rahman (UTAR). IT can be the students from any faculty or stream, including Foundation, Postgraduate, Master's or PhD levels. Nevertheless, the respondents were required to meet specific criteria to ensure their relevance to the research objectives. Before answering the questionnaire, the participants should ensure that they are (1) enrolled as UTAR students at the time of data collection, and (2) must be at least 18 years old to provide informed consent. No prior experience using AI tools or applying them in investment activities is required, as the study focuses on students' intention rather than their practical usage. Students meeting these criteria will be eligible to participate in the online survey, regardless of their faculty, year of study, or campus location (Kampar or Bandar Sungai Long).

3.6.2 Sampling Technique

The data for this paper were collected using the convenience sampling method, a type of non-probability sampling method (M. S. Hassan et al., 2023). Rahi (2017) defines convenience sampling as the practice of gathering data from a research population that is easily accessible to the researcher. Since convenience sampling basically entails using a sample that is easily accessible, it can be used in practically any type of research.

Some researchers frequently employ this kind of sampling technique to assess and examine participants' propensity to adopt the new technology (M. S. Hassan et al., 2023; Namahoot & Jantasri, 2022). Most of the important reasons are that these techniques do not require the researcher to compile a list of every component of the population (Alvi, 2016), which is important as the full list of UTAR students is private and cannot be obtained. In addition, Koerber and McMichael (2008) note that this approach works well when researchers are unable to choose volunteers from a variety of populations or study locations, which aligns with the present study’s focus solely on UTAR students. Another reason that drives to utilization of this kind of sampling method is that it can help researchers save effort when choosing participants as opposed to using other non-random selection methods. Next, convenience sampling that allows the researcher to select participants at a very low cost also encourages to use of this method in the present research (Sedgwick, 2013). Morover, the researchers spend less time due to the easy access to the sample drawn from the target demographic. Lastly, this method also gives an opportunity to the researcher to receive all or almost all the questionnaires back, encouraging a good response rate (Bryman & Bell, 2011).

3.6.3 Sampling Size and Power Analysis

If researchers study the full population of interest, they will obtain more reliable findings. However, in most cases, a study of the entire population is not practical in most circumstances, if not impossible, and would be inefficient. Since analysing the chosen sample is more accurate compared to studying the total population, several researchers will apply various techniques to identify their samples to represent the entire population. In this way, the researchers can estimate the overall population parameter by examining the data from the chosen samples. Hence, it is crucial to choose a correct sample size in order to answer the research question (In et al., 2020; Kang, 2015). On record, there are around 20,000 students at Universiti Tunku Abdul Rahman for the year 2025. According to Krejcie and Morgan (1970), the minimum recommended sample size for a population of at least 20,000 is 377 at an 85% confidence level with a 5% margin of error.

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

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

Source: Krejcie & Morgan, 1970

Figure 8: Minimum Sample size based on Krejcie and Morgan (1970)

Meanwhile, this research has also calculated the sample size with eh G power, which has been used by some of the earlier scholars like (Bajunaied et al., 2023; Shiva et al., 2023; Eren, 2023). The utilization of the G power is due to G* Power analysis can ensure that the study has sufficient power to detect meaningful relationships between independent variables (PU, PEOU, ATT, FC, SI, HA, P, HM, GNDR) by entering parameters such as effect size, alpha level (the probability of a Type I error), power (the probability of correctly rejecting the null hypothesis), and the number of predictors (Buchner et al., 2020). Along with this, the G*Power software's ease of use in determining sample size and power for different statistical techniques has prompted researchers to use it to analyze their research sample size . Besides, this kind of software that opens access for everyone has also boosted its adoption (Kang, 2021).

In this study, the G*Power software indicates that the minimum sample size requirement at a 5% significance level for a medium effect size of 0.15 is 172 respondents (Figure 9). Hence, it can be concluded that the sample size of 300 respondents in this study is sufficient for hypothesis testing and conducting a meaningful analysis.

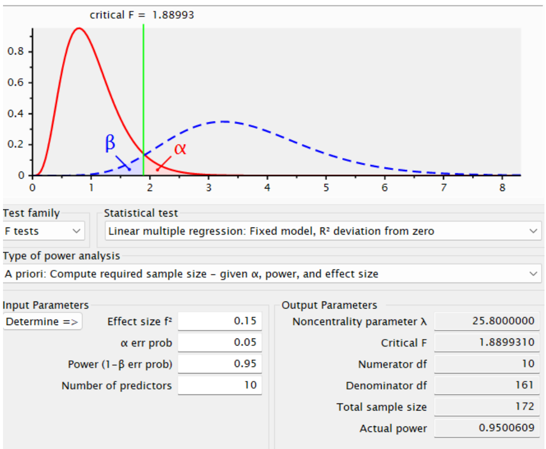


*Figure 9: G*power analysis*

3.7 Operational Definition of Research Model Constructs

An Operational Definition refers to a description of the steps and metrics that are used to convert an intangible idea into measurable indications (Bryman & Bell, 2011). According to Sekaran (2003), operational definition is the process of giving a concept a measurable form by examining the behavioral aspects, dimensions, or characteristics that the term represents. The majority of the constructs used include perception, knowledge, underlying principles, and religion. Constructs are fundamental concepts used in research and often explained in a theoretical context. However, the constructions of the actual and perceptible things may not have physical manifestations, meaning it can be abstract. Because constructs cannot be directly viewed or measured, it is known as latent variables. Then, there are several variables used when measuring the constructions (Kant, 2023). The constructs also serve as foundation for developing working hypotheses that guide researchers in examining and understanding the relationship between study variables.

The operationalisation of variables in the proposed research model and hypotheses is based on well-established models that have been mentioned in Chapter 2, which are the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2003; Venkatesh et al., 2012). These frameworks have been widely validated in technology adoption studies and provide reliable scales for constructs such as perceived usefulness, perceived ease of use, social influence, facilitating conditions, habit, hedonic motivation, price value, and behavioral intention. Measurement items were adapted from prior validated studies and modified to suit the context of university students' intention of AI-driven tools in investment strategies. The following are the operational definitions of the dependent and independent variables:

a) Behavioral Intention (BI)

The operational definition of behavioral intention (BI) refers to the degree to which UTAR students have consciously formulated plans to adopt and use AI-driven tools in their investment decision-making (Davis, 1985, p. 214; Papathomas et al., 2025; Dixit et al., 2025; Du et al., 2025; Ammenwerth, 2019; Chatterjee & Bhattacharjee, 2020; Hu et al., 2025; Alwakid et al., 2025; Roy et al., 2022; AlAmayreh et al., 2023; Roh, T., & Xiao, S., 2023)

b) Perceived Usefulness (PU)

The perceived usefulness (PU) of this paper is determined as the UTAR students' belief that AI-enabled tools will enhance their investment performance in some meaningful way (Singh & Kumar, 2024; Almajali et al., 2022; Amayreh et al., 2023; AlAmayreh et al., 2023; Liu et al., 2023; Nainggolan and Handayani, 2023; Pusposari et al., 2024; Belanche, Casaló, and Flavián, 2019)

c) Perceived Ease of Use (PEOU)

Perceived Ease of Use (PEOU) means the degree to which UTAR students believe that using AI-driven tools in financial investment is free of physical and mental effort (Nainggolan and Handayani, 2023; Roy et al., 2022; Almajali et al, 2022; J. Park et al., 2024; Setiawan and Setyawati, 2020; Belanche et al., 2019; Lu et al., 2005)

d) Facilitating Conditions (FC)

In this study, facilitating conditions (FC) refer to whether UTAR students believe that sufficient resources, support, and technical infrastructure are in place to enable their use of AI-driven tools in financial investment (Venkatesh et al., 2003; Pipitwanichakarn and Wongtada, 2021; Geng et al., 2021; Fang et al., 2025; Noreen et al., 2023; Roh et al., 2023; Yeh et al., 2022).

e) Social Influence (SI)

The operational definition of social influence (SI) refers to the degree to which UTAR students perceive that important people around them, such as peers, family, or friends, believe they should adopt AI-driven tools in investment management (Yeh et al., 2022; Aksoy et al., 2020; Chung et al., 2017; Fang et al., 2025; Venkatesh et al., 2003).

f) Price Value

In this study, price value (P) refers to the extent to which UTAR students believe that the benefits of using AI-driven tools in financial investment outweigh any potential costs associated with them (Ain et al., 2016; Venkatesh et al., 2012; Bhatia, Chandani, Atiq, et al., 202; Ahmed et al., 2024; Alzyoud et al., 2024).

g) Habit

The habit is determined as the extent to which UTAR students' prior experiences and repeated behaviours influence their willingness to use AI-driven tools in their investment strategies (Venkatesh et al., 2012; Ajzen, 1991; Zhafira et al., 2025; Mittal, 1988; Ouellette and Wood, 1998; Papathomas et al., 2025; Dixit et al., 2025).

h) Hedonic Motivation

Hedonic Motivation in this research is defined as the enjoyment or pleasure that UTAR students derive from using AI-driven tools in financial investment, which reflects their intrinsic motivation to adopt such technology (Brown and Venkatesh, 2005; Jegerson et al., 2023; Alzyoud, Alshurafat, and Khatatbeh, 2025; Salimon et al., 2017; Gawior et al., 2022; Siyal et al., 2020; Ahmed et al., 2024; Marak et al., 2025)

i) Demographic variable

In this study, demographic variables refer to the socio-demographic characteristics of university students, specifically their gender. These variables are included to examine potential differences in the behavioral intention of AI-driven tools for financial investment (Kuo et al., 2009; Schermerhorn et al., 2008; Méndez-Suárez et al., 2023; Terzis and Economides, 2011; F. Wang et al., 2023**;** Parlangeli et al., 2023).

j) Attitude (ATT)

In this study, the attitude (ATT) is defined as the positive or negative feelings of UTAR students towards the AI-driven tools in their investment strategies (Roy et al., 2022; Fishbein et al., 1975; Manrai & Gupta, 2022; Ikhsan et al., 2024;Chong et al., 2021;Singh and Kumar, 2024; Roh et al., 2023)

In order to measure these variables, all measurement items were carefully adapted and revised from established scales to ensure reliability and validity. The questions were modified to suit the context of UTAR students' intention of AI-driven tools in financial investment, thereby guaranteeing that appropriate responses can be captured to address the research questions and objectives of this study. The tables below provide a summary of the constructs and the corresponding measurement items.

Table 3.1: Measurement of constructs

	Constructs	Items	Description of Items	Measurement	Sources
1.	Behavioural Intention (Adapt)	BI1r BI2r BI3r	I intend to keep using AI investment tools for making sustainable investment decisions. I would recommend others to use AI investment tools for making sustainable investments. I think I am going to use AI technology in future trading.	From 1=strongly disagree to 5=strongly agree	Mohapatra et al. (2025), AlAmayreh et al. (2023)
2.	Attitude (Adapt&Adopt)	ATT1r ATT2r ATT3p ATT4r	I have a positive impression of AI-based investment applications and platforms overall. Utilizing the AI-based application and platforms appears to be a favorable decision. The use of AI technology is a good concept. It is a clever choice to use AI-based investment tools over other traditional services.	From 1=strongly disagree to 5=strongly agree	Bernice et al (2024), AlAmayreh et al. (2023)
3.	Perceived Usefulness (Adapt)	PU1r PU2r PU3r PU4r	The AI investment tools enhance my efficiency in making better, sustainable investment decisions. The AI-based investment platform provides me with valuable information about investment market opportunities The AI tools improved my skills in conducting investment transactions AI investment tools have empowered us to make faster and more data-driven decisions	From 1=strongly disagree to 5=strongly agree	Nainggolan and Handayani (2023), Mohapatra et al. (2025)

		PU5r PU6r PU7r PU8r	AI investment tools have allowed us to make more informed and timely investment decisions. AI investment tools allowed us to improve our risk management and identify potential risks that may be overlooked by human analysts AI investment tools have enabled us to identify undervalued assets that may not be easily detectable using traditional methods The AI investment tools is helpful in aligning my investment strategy with sustainability.		
4.	Perceived Ease of Use (Adapt & Adopt)	PEOU1p PEOU2r PEOU3p PEOU4p PEOU5p PEOU6p	AI technology would not be easy for me to learn. My interaction with AI investment tools does not need me to think too much. AI technology use in my AI tasks completion is easy. Interaction using AI technology seems flexible I think I can master AI technology. I believe using AI technology would be simple.	From 1=strongly disagree to 5=strongly agree	AlAmayreh et al. (2023)
5.	Facilitating Condition (Adapt)	FC 1r FC2r FC3r FC4r	I possess the requisite resources to utilize the AI investment tools. I possess the necessary knowledge to make use of the AI-based investment application and platforms. If I face any challenges while using the AI-based investment application and platforms, I can seek assistance from others.	From 1=strongly disagree to 5=strongly agree	Bernice et al (2024), Dixit et al. (2025),

		FC5r	AI-based investment platforms and applications are regularly updated and improved, making them more user-friendly for investment activities. AI-based investment platforms and applications offer clear instructions and guidance on how to effectively use their features for investment decisions.		
6.	Social Influence Adapt)	SI1r SI2 r SI3r SI4r SI5r SI6r SI7r	When I see that AI investment tools are recommended to me based on the preferences of other users, I feel more confident in using them. I am influenced by the popularity of AI investment tools among other users when deciding whether to use them. AI investment tools are more appealing to me when I see that they have been endorsed or shared by friends or peers on social media. I utilised the AI-based investment trading applications and platforms to follow my peers. Due to my lack of investment knowledge, I used an AI-based investment application and platforms when trading. My family thinks that using an AI-based investment platform is a good idea. Most of my friends would use AI investment tools for trading.	From 1=strongly disagree to 5=strongly agree	Dixit et al. (2025), Nainggolan and Handayani (2023), Bernice et al (2024), Kenesei et al. (2025)
7.	Habit (Adapt)	HA1r HA2r HA3r	Using AI tools has become a habit for me when trading. It has been natural for me to use AI investment tools. I am addicted to using the AI investment tools. I feel I need to use AI tools when trading.	From 1=strongly disagree to 5=strongly agree	Al-Okaily et al. (2025), Venkatesh et al. (2012)

8.	Hedonic Motivation (Adapt & Adopt)	HM1r HM2r HM3p HM4r	I derive satisfaction from discovering unique and personalized investment recommendations that enhance my trading experience. The AI tools in the investment applications and platforms make me happy with my investment choices. I believe that using Artificial Intelligence will be annoying. Using the AI investment tools is very entertaining.	From 1=strongly disagree to 5=strongly agree	Bernice et al (2024), Dixit et al. (2025), Papathomas et al. (2025),Venkatesh et al. (2012)
9.	Price Value (Adapt)	P1r P2r P3r P4r P5r P6r	AI-based trading application and platforms have helped us execute trades more efficiently and reduce transaction costs. The AI-based trading applications and platforms offered competitive investment prices for students. The satisfaction with the benefits I received from using the AI tools is higher. The benefits provided by the AI investment tools encourage me to invest further. The value I receive from the AI investment tools justifies its cost. At the current price, AI investment tools provide a good value	From 1=strongly disagree to 5=strongly agree	Bernice et al (2024), Alfzari et al. (2025),Venkatesh et al. (2012)

3.8 Questionnaire Design

A questionnaire is a s a self-administered instrument for gathering data that is typically provided on paper or electronically, such as a Google Form. Its main objective is to directly gather information from participants by asking them pre-written questions designed to meet the objectives of the study. Researchers can gather both subjective and objective data—such as personal opinions and views, as well as demographic characteristics and behaviors—by using questionnaires (Kant, 2023). According to Vannette & Krosnick (2019) and Malhotra (2006), the most common method of gathering primary and quantitative data is through questionnaires, which standardise and compare the data collection process. Taherdoost (2022) also has stated that it is one of the most dominant ways of implementing surveys in a distinct scope of study, including academic studies, commercial enterprises, and governmental institutions. The questionnaire is divided into two groups, which are open-ended and closed-ended questions.

The questionnaire of this research is divided into three sections. For Section A, it is related to the it is about demographic questions, including the age, gender, faculty, ethnic group, religion, educational level, and previous investment experience. This kind of question is more related to a personal factual question, which requests respondents' private information (Kant, 2023). However, people are typically reluctant to answer specific queries related to their personal information, such as age and income, and eventually asking questions about these subjects can demotivate them. To address this issue, applying ranges rather than precise values for the options is recommended (Agrawal, 2010). Therefore, the question of age has application ranges such as 18-20, 21-23, 24-26, etc. Although the income level questions were asked by a lot of prior scholars who had done research related to investment, the present paper did not include them because it was considered too private, which might lead to the respondents refusing to answer the questions.

Next, Section B is the general question that relates to the awareness of AI tools in investment strategies. This general question aims to understand how deeply the students know about the AI-enabled tools. It also serves as a ‘warm-up’ for the respondents before asking the specific questions (Bryman & Bell, 2011). Finally, Section C contained items measuring the main constructs of the research model, including Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Habit, Hedonic Motivation, Price Value, and Behavioural Intention to adopt AI-driven tools. All items in Section C were measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

3.9 Pre-testing

The pre-testing is implemented after the questionnaire has been conducted. This procedure is crucial to improve readability, reduce the cognitive load on respondents and foster clarity (Chau et al., 2025). During the pre-test, respondents are encouraged to ask the researcher questions if they face any difficulties in understanding the questionnaire items. This feedback allows the researcher to identify potential problems (X. Hong et al., 2023). On the other hand, even though the questionnaire is clear and easy to understand, some respondents may still be reject to complete it due to too lengthy. Therefore, conducting a pre-test can help the researchers assess and manage the survey length to enhance the willingness to participate of respondents (Winata & McLafferty, 2025). For the present study, the questionnaire will be pre-tested with 10 UTAR students to ensure that the questions are clear, the structure is manageable, and the overall instrument is valid for use in the main data collection.

3.10 Research Ethics

Respecting and upholding respondents' rights (particularly the rights of privacy and confidentiality is quite important in survey research. (Meadow et al., Chapter 5, Ethics). Before answering the questionnaire, participants must be informed of the survey's objectives, its intended use, and whether their answers will be kept private.

Before beginning the data collection, the researcher must obtain approval from the Research Ethics Committee, Institute of Postgraduate Studies and Research (IPSR) of Universiti Tunku Abdul Rahman (UTAR) to confirm the questionnaire design and data collection procedures. In addition, the researcher will also provide the consent form to the respondents on the first page of the questionnaire to guarantee that the participant is voluntarily involved and fully informed about the study's objectives. Besides, offering the consent form is also intended to protect the respondent's rights by allowing withdrawal at any time, as well as safeguarding the confidentiality of their responses. Therefore, the results from the participants will not be harmed. Overall, these measures uphold ethical standards and strengthen the credibility of the research.

3. 11 Data Analysis

3.12.1 Descriptive Statistic

Descriptive statistics is a fundamental area of study in statistics. It shows how variables relate to one another in a sample and is frequently used to clean up as well as compile dispersed data, which is essential for research and inferential statistical comparisons (Kaur et al., 2018). A statistical model reflects the prior understanding of the probability experiment that yielded the observed data (Bijma et al., 2017). Many descriptive statistics ideas can also be identified using basic calculus, like mean, mode, median, standard deviation, and variance. Besides, Skewness, frequency, and range are also significant in analyzing data. In this study, the researchers will present the descriptive statistics (mean, mode, median, standard deviation, and frequency) for all eleven constructs. At the same time, it also involves the demographic profile, like age, region, ethnic groups, and previous investment experiences. Below represents the formula of the descriptive statistics:

i) Mean ($\bar{x}$)

$$\frac{\sum x}{N} \qquad (3.3)$$

Where:

$\sum x$ = Sum of all the data points

N = Number of data points

ii) Median

Odd:

$$\frac{(n+1)}{2} \qquad (3.4)$$

Even:

$$\frac{\left(\frac{n}{2}\right)+\left(\frac{n}{2}+1\right)}{2} \qquad (3.5)$$

Where:

n= number of observations

iii) Standard Deviation (σ)

$$\sqrt{\frac{\sum(X-\bar{x})^2}{n-1}} \qquad (3.6)$$

X = Value in the data distribution

$\bar{x}$ = Sample Mean

n= Total number of observations

3.11.2 Reliability Test

The evaluation model applied in this study is consistent with the SPSS model described by Hair et al. (2014). Using techniques to assess validity and reliability is crucial to maintain the precision of the relationship that has been built. These procedures include examining indicator reliability and evaluating internal consistency reliability (Chau et al., 2025). Reliability describes the measurement consistency and the extent to which an instrument produces comparable outcomes when utilized in the same circumstances. (Kangu, 2017). The primary method used to measure the internal consistency reliability is Cronbach's alpha. To ensure internal consistency of the measurements, the Cronbach's α values must be more than 0.7 (Nunnally, 1978).

3.11.3 Statistical Package for the Social Sciences (SPSS)

The statistical software that employs in the current study is Statistical Package for the Social Sciences (SPSS) version 27 that introduced by Norman H. Nie, Dale H. Bent and C. Hadlai Hull in 1968 to analyse the collected data (McCormick et al., 2015). Other than SPSS, there generally has a lot of the data analysis software that can be used by researchers for quantitative analysis, such as SEM, Stata, Splus, Excel and Jefferys's Amazing Statistics Program (JASP) etc. However, the SPSS in chosen as the software in this study is because of its user-friendly design and powerful data management compared the other software. There are no requirements for the programming language when using SPSS to analysed data since it is designed for non-technical persons, particularly those in the social sciences. Also, it can run on any hardware platform such as Windows, macOS, and Linux, increasing the accessibility of users (Rahman & Muktadir, 2021).

Quantitative analysis is required the researchers to gather the data from a larger size of the respondents to ensure the accuracy and reliability of findings. However, SPSS also has the ability to handle vast amount of the data set with multiple variables connected to it (Foster, 2001). Besides, it also performs well in data analyses process, including data preparation, management, analysis and reporting by automatically determining the abnormalities and statistical transformations to manage the potential outliers. Additionally, this software also will provide a clear and effective table, graph or visualization, enhancing the presentation and interpretation of result. Furthermore, SPSS also enable accurate modelling of both linear and non-linear relationships, leading to it serve as a comprehensive tool for quantitative analysis (Rahman & Muktadir, 2021).

3.12.4 Multiple Regression Analyses

The statistical technique that applied in this study is Multiple Regression, which is a part of the general linear model that allows the researchers to examine the relationship between one dependent variable and two or more independent variables. Unlike the ANOVA technique, it can help to manage the categorial and continuous predictors. Plus, user-friendly also is another factor that it has been chosen for the present research, meaning that multiple regression is easy to integrate with 2 or more independent variables (Keith, 2015).

According to this technique, the researchers can obtain several of statistical results, like R^2, Adjusted R^2, F-value, Standardised and Unstandardized Coefficients, etc. R^2 can be defined as "an estimate of variance in the dependent variable that can be explained by all the independent variables in the model", which offers the whole information of a regression model. But a high R^2 does mean that the model performs well, as the performance of the model still relies on dependent variables to be explained. Then, the F-value presents the significance of the whole model, indicating that a higher F-value can explain a significant amount of variance in the dependent variable. Unstandardized coefficients (B) is referred to the real change in the dependent variable when the independent variable changes by 1 unit, while the standardised coefficients (β) make it possible to compare the relative impact of predictors on different measurement scales (Keith, 2015).

In order to ensure the precision of the findings, the researchers need to ensure that all the assumptions of the multiple regression model are met, involving normal distribution, linearity, multicollinearity, homoscedasticity, and autocorrelation. If the model violates these assumptions, it can lead to the R^2, test of statistical significance, regression coefficients, and standard errors being biased. Therefore, the preliminary analyses were conducted to avoid a serious violation from happening (Keith, 2015).

3.13 Conclusion

Chapter 3 presented the research method that was applied to ensure the achievement of the objective, including the research paradigm, research design, sample, development of framework and hypothesis, data collection method, and operational definition of research model constructs. Through distributing the questionnaire via social media platforms and offline methods, 210 of the UTAR students participated in this study, which fulfilled the threshold of G*Power. The collected data will then be managed and analysed using SPSS, which is a tool that is quite easy to use for inexperienced researchers.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter presents the data analysis collected from UTAR students through the survey questionnaire. First of all, the demographic profile and the awareness of the respondents are summarised using descriptive statistics. Next, the central tendency measurements, including the mean and standard deviation for all constructs, will be reported in this study. Following this, the diagnostic tests were conducted to ensure the model fulfils the assumption in SPSS. Subsequent sections focus on the inferential analysis used, which draws the conclusions regarding the characteristics of the young investor based on UTAR students. Other than that, this kind of analysis also investigates the relation to the research questions and hypotheses mentioned in Chapters 1 and 2. All the analyses in this chapter are conducted using the Statistical Package for the Social Sciences (SPSS).

4.1 Descriptive Analysis

4.1.1 Demographic Profile

The respondents' demographic profile is summarised in Table 4.1. This table presents the frequency (n) and percentage (%) for each category of gender, age, faculty, ethnic group, religion, education level, and investment experience. While the awareness of the respondents about the AI investment tools is compiled in Table 4.2. This table reports the frequency (n) and percentage (%) of familiarity with, use of, and experience with AI-powered investment tools are compiled

In this research, a total of 210 UTAR students were collected via the survey questionnaire. This questionnaire was distributed using social media platforms such as RedNote, Instagram, WhatsApp, as well as through offline methods. According to Table 4.1, the findings show that the majority of the respondents were female (67,6%, n=142), while males only occupied 68 (32.4%). In other words, the female respondents formed more than two-thirds of the sample. Moreover, the majority of the respondents were between 21- 23 years old (57.6 %, n=121). This was followed by the respondents aged 18-20 years old (22.9%, n=48), as well as 24 and above (19.5%, n=41). This finding suggests that the sample mainly involves young adults in early adulthood.

The participants of this study come from diverse faculty across the university. The largest proportion was from the Faculty of Accountancy and Management (Sungai Long) with 42.9% (n=90). Following this, Lee Kong Chian Faculty of Engineering and Science accounted for 13.8% (n=29), constituting the second-largest proportion. Compared to these two faculties, the remaining faculties each accounted for a small proportion, with the number of respondents not exceeding 10 and the percentages below 10%. Since the research is targeted at UTAR students, most of the respondents are Chinese, who represented 94.8% (n=199) of the total. While the Indians and Malays occupy 4.8% (n=10) and 0.5% (n=1) respectively. This result led to Buddhism being reported as the majority religion, which represents 71.9% (n=151) compared to other religions. This was followed by Christianity (17.6%, n=37), Hinduism (5.7%, n=12) and Islam (5%, n=1).

Nonetheless, there was a small portion of them that were identified as Others (including Taoism or Non-believer), representing 4.3% of samples with 9 respondents. For the education level, most respondents were undergraduate students, representing 86.2%(n=181) compared to foundation students (9%, n=19), master's degree or Doctorate/PhD level students (4.8%, n=10). The survey findings also show that most of the UTAR students have limited investment experience (50.6%, n=106). About 31.4 % (n=66) have less than 1 year of experience, and 14.3% (n=30) have

1-3 years of experience. Few of them have long-term experience, with evidence showing only 38 students having more than 1 years.

Table 4.1: Demographic Profile

Characteristics	%	n	Characteristics	%	n
Gender			**Ethnic Group**		
Female	67.6	142	Malays	0.5	1
Male	32.4	68	Chinese	94.8	199
			Indians	4.8	10
Age Group			**Religion**		
18-20	22.9	48	Muslim	5	1
21-23	57.6	121	Buddha	71.9	151
24 and above	19.5	41	Hindu	5.7	12
			Kristian	17.6	37
			Others	4.3	9
Faculty			**Education Level**		
Faculty of Accountancy and Management (Sungai Long Campus)	42.9	90	Foundation	9	19
Lee Kong Chian Faculty of Engineering and Science	13.8	29	Undergraduate	86.2	181
Others	42.3	91	Master's Degree and PhD/Level	4.8	10
Investment Experience					
None	50.5	106			
Less than 1 year	31.4	66			
Above 1 year	18.1	38			
Total	**100**	**210**		**100**	**210**

Source: Designed for this study

4.1.2 Awareness

According to Table 4.2, a significant proportion of respondents (39%, n=82) reported that they have no use for the AI investment tools, while the remaining 61% are familiar with at least one tool. Compared to all the tools, UTAR students have the highest familiarity with Moomoo Malaysia-Moomoo AI (46.2%, n=97). Other tools such as A Stock Master (12.9%, n=27). The remaining tools are the less commonly known tools among the students included Wahaed Invest, TipRanks, Daloopa, StockInsight AI, other specialised platforms such as StashAway Robo-advisor and etc, as evidenced by their percentage being smaller than 5%.

In the context of the actual usage of AI tools, 48.6% (n=102) of the respondents have not used any AI investment tools, suggesting that familiarity does not always translate into usage. However, the most used tool was again Moomoo Malaysia- Moo AI (34.8%, n=73), and followed by AI Stock Master (13.3%, n=28) But the remaining tools were used by a small proportion of the respondents (<5%).

The result also shows that there is around 50.5% UTAR students do not have prior experience with AI-powered investment tools. 36.2% reported using these tools for less than 1 year, while only 10.5% had used 1 to 3 years. Then, there are a very few respondents had a long-term use, as evidenced by 30 out of 210 students had adopted the tools more than 1years.

Overall, the data indicates that although many UTAR students are aware of the popular AI investment tools, the actual usage remains limited. Most of the students have minimal experience, with 86.7% having less than 1 year of usage or not using at all. This demonstrated that AI adoption in investment strategies among UTAR students is still at an early stage.

Table 4.2: Awareness about AI tools in Investment Strategies

Respondents' Familiarity	**%**	**n**	**Actual Usage of AI tools**	**%**	**n**
Do Not Use	39	82	Do Not Use	48.6	102
Moomoo Malaysia	46.2	97	Moomoo Malaysia	34.8	73
AI StockMaster	12.9	27	AI StockMaster	13.3	28
Others	57.2	122	Others	42.7	89
Investment Experiences					
None	50.5	106			
Less than 1 year	36.2	76			
Above 1 year	13.3	28			

<u>Source:</u> *Designed for this study*

4.2 Central Tendency Measurement and Scale Measurement

This study has measured a few of the constructs related to respondents' intentions, including behavioural intention (BI), perceived usefulness (PU), perceived ease of use (PEOU), price value (P), habit (HA), and Social Influence (SI), hedonic motivation (HM), facilitating condition (FC), and attitude (ATT). The descriptive statistics and reliability test of this study are presented in Table 4.3.

Based on Table 4.3, the mean scores of all constructs range between 3.560 to 4.015. This result indicates that UTAR students generally expressed moderate to high agreement with items measuring their intention of using AI tools in investment strategies. In comparison, Behavioral Intentions (BI) had the highest mean (μ= 4.015), showing a strong intention among UTAR students to adopt the AI tools to manage their portfolio or investment strategies. Similarly, Perceived Usefulness (PU) (μ=4.012), Attitude (ATT)(μ=4.013), and Price Value (P) (μ=4.005) were also rated highly. This implies that students often see the AI tools as useful and provide reasonable value, and hold a favourable attitude toward utilising the tools in their investment activities. Furthermore, constructs such as Social Influence (SI) (μ=3.913), Hedonic Motivation (HM) (μ=3.935), and Facilitating Condition (FC) (μ=3.93) are scored as moderately high, which implies UTAR students experience some degree of social encouragement to use AI tools, enjoy using and perceive that enough technological or resource is available. Also, Perceived Ease of Use (PEOU) recorded a moderately high score with the mean value of 3.855, suggesting that UTAR students find the AI tools easy to use. On the other hand, Habit (HA) has the lowest mean scores of 3.560, indicating that UTAR students have not yet developed robust habitual behavior when using AI tools for their investment activities.

In terms of variability, the standard deviation for all constructs ranges from 0.89 to 1.18. Comparability, Habit has displayed the highest variability. This indicates that UTAR students have a different level of routine use of AI tools. In contrast, other constructs is more consistent responses across UTAR students. Regarding reliability, the findings also show that the constructs have strong internal consistency. This is supported by Cronbach's Alpha values of the constructs, which fall between 0.888 to 0.955, all of which exceeded the widely accepted reliability benchmark of 0.7 (1-s2.0-s245195; Hair et al., 2017). Hence, it can be confirmed that the measurement items of this study are highly reliable.

Table 4.3 Descriptive statistics in the constructs and Cronbach's Alpha

	Item	Mean	Std.Deviation	Cronbach's Alpha
Behavioral Intention	7	4.015	0.918	0.951
Perceived Usefulness	8	4.012	0.890	0.955
Perceived Ease of Use	5	3.855	0.970	0.888
Price Value	6	4.005	0.930	0.945
Habit	4	3.560	1.180	0.928
Social Influence	7	3.913	0.956	0.938
Hedonic Motivation	3	3.935	0.947	0.89
Faciliting Condition	5	3.930	0.954	0.927
Attitude	4	4.013	0.931	0.917

Source: *Designed for this study*

4.3 Preliminary Analyses

Before conducting the main findings analyses, preliminary checks are a key step that needs to be performed to guarantee that the collected data have met the assumptions for the multiple regression analysis. The processes include the assessment for autocorrelation, multicollinearity, normality, linearity and homoscedasticity. According to the above tables, there is no autocorrelation and multicollinearity in models 1 and 2. This is because the Durbin-Watson statistic for both models is close to the ideal value of 2, and their VIF values are smaller than 10 (Moran, 2025). Besides, both models also have a normal distribution, linearity and homoscedasticity were met based on visual inspection of residual plots (refer to appendix 1 until 5). In conclusion, models 1 and 2 fulfil the assumptions for regression analysis, ensuring the reliability of the subsequent analyses.

Table 4.4 Durbin Watson and VIF for Model 1

	Durbin-Watson	VIF
PU→BI	2.122	4.165
PEOU→BI		3.656
SI→BI		3.496
FC→BI		4.366

Source: *Designed for this study*

Table 4.5 Durbin Watson and VIF for Model 2

	Durbin-Watson	VIF
P→BI	1.964	4.627
HA→BI		1.781
HM→BI		3.633
ATT→BI		4.651
GNDR→BI		1.010

Source: *Designed for this study*

4.4 Inferential Analyses

4.4.1 Regression Analysis

For model 1, a multiple regression analysis was conducted to examine the relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Facilitating Condition (FC), and Social Influence (SI) and students' attitude (ATT) towards AI tool adoption in investment strategies among UTAR students. The overall regression model was statistically significant as this model has a high F-value and a p-value smaller than 5% ($F = 214.86, \rho < 0.001$),indicating that the combination of PU, PEOU, FC and SI significantly predicts the attitude towards AI investment tools among UTAR students. Referring to the guidelines given by Valle et al. (2024), the R^2 values are categorised as moderate (0.5), weak (0.25) and considerable (0.75). In this study, the R^2 of model 1 is 0.807, which means that 80.7% of the variance in the attitude of UTAR students towards using AI tools in their investment strategies is explained by all the PU, PEOU, FC and SI. The high value implies that the model provides a strong predictive ability and is considerable level of explanatory power.

Specifically, Perceived Usefulness (PU) had a strong and positive effect on Behavioral Intention (B=0.614, β=0.587 and ρ<0.001), supporting H1 (PU→ATT). Similarly, H3 (FC→ATT) is supported as the result demonstrates that the Facilitating Condition (FC) has a significant positive influence on attitude (ATT) (B=0.216, β=0.222 and ρ=0.001). In contrast, Perceived Ease of Use (PEOU) and Social Influence (SI) were not statistically significant effects on ATT with β=0.03 and ρ>0.05 and β=0.11 and ρ>0.05, respectively. Therefore, H2 (PEOU→ATT) and H4 (SI→ATT) were not supported.

Table 4.6: Coefficient of Determination of Attitude

	Unstandardized Coefficients		**Standardized Coefficients**		
Model 1	**B**	**SE B**	**β**	**ρ-value**	**Significant**
(Constant)	0.170	0.134		0.208	
Perceived Usefulness	0.614	0.065	0.587	0.000	H1 Supported
Perceived Ease of Use	0.029	0.056	0.030	0.608	H2 Not Supported
Facilitating Conditions	0.216	0.063	0.222	0.001	H3 Supported
Social Influences	0.107	0.056	0.110	0.056	H4 Not Supported

Dependent Variable: Attitude, SEB 0.3929
Note: R^2=80.7%, Adjusted R^2 =80.4% F = 214.86**, *ρ< 0.05, ***, ρ< 0.001
Source: Designed for this study

For model 2, a multiple regression analysis was undertaken to examine the effects of Price Value (P), Habit (HA), Hedonic Motivation (HM), Attitude (ATT) and Gender (GNDR) on Behavioral Intention of UTAR students to use the AI investment tools for managing their portfolio or trading. Based on the result, the overall regression model is statistically significant as it has a high value of R^2 and F-value (R^2=82.1%, F = 187.39), as well as its ρ-value is larger than 0.05. The result also reflects that this model has a considerable level of explanatory power.

Specifically, Prive Value(P) has a significant positive effect on BI (B=0.348, β=0.352 and ρ<0.001), supporting H5 (P→BI). Habit (HA) also has a significant positive but smaller influence on BI (B=0.061, β=0.079 and ρ=0.048), supporting H6 (HA→BI). While Hedonic Motivation (HM) significantly predicts BI of UTAR students (B=0.134, β=0.138 and ρ=0.015), supporting H7 (HM→BI). On top of that, the Attitude (ATT) of UTAR students towards the AI-based investment tools is a robust and significant predictor (B=0.403, β=0.408 and ρ<0.001), supporting H8 (ATT→BI). However, Gender (GNDR) does not significantly affect BI as its ρ-value is larger than 0.05, leading to rejection of H9 (GNDR→BI).

Table 4.7: Coefficient of Determination of Behavoiral Intention

	Unstandardized Coefficients		**Standardized Coefficients**		
Model 2	**B**	**SE B**	**β**	**ρ-value**	**Decisions**
(Constant)	0.250	0.128			
Price Value	0.348	0.063	0.352	0.000	H5 Supported
Habit	0.061	0.031	0.079	0.048	H6 Supported
Hedonic Motivation	0.134	0.055	0.138	0.015	H7 Supported
Attitude	0.403	0.063	0.408	0.000	H8 Supported
Gender	0.039	0.058	0.020	0.501	H9 Not Supported

Dependent Variable: Behavioral Intention; SE= Std. Error
Note: R^2=82.1%, Adjusted R^2= 81.7% F = 187.39**, *ρ< 0.05, ***, ρ< 0.001
Source: Designed for this study

4.4.2 Discussion

The findings reveal that Perceived Usefulness (PU) significantly influences UTAR students' attitudes toward adopting AI investment tools, supporting H1 (PU→ATT). This is consistent with the previous studies. For instance, Noreen et al. (2023) and Dang et al. (2025) both reported that investors who perceived AI-powered financial tools as practical, dependable and efficient are more inclined to incorporate these tools into their decision-making processes. Similarly, Papathomas et al. (2025) also found that an AI-based system can help users in simplifying complex decisions, thereby improving user confidence. For the current study, UTAR students develop a favourable attitude when they find that AI investment tools can enhance convenience and accuracy by providing faster and informed investment decisions. They also believe that the AI investment tools enabled them to identify undervalued assets which may not be detectable using traditional methods, leading to a high intention to use them.

Nevertheless, the present study found that perceived Ease of Use (PEOU) did not significantly affect attitudes towards adoption of AI tools in investment strategies among UTAR students, leading to rejection of H2 (PEOU→ATT). This result does not align with traditional technology acceptance theories but is supported by a few of the prior studies such as Eren (2023); Singh and Kumar (2024); and Bernice et al. (2024). Based on Eren (2023), respondents who lack familiarity or have no knowledge and experience will be difficult to accurately judge how easy the tools are to use. Therefore, the ease of use may not yet be a meaningful factor in shaping the UTAR students' attitudes towards AI investment tools, as the AI investment platforms are still relatively new and most of them are inexperienced about this new technology.

H3 (HM→BI) is supported, meaning the Facilitating Condition (FC) was found to have a significant positive impact on UTAR students’ attitude toward AI investment tools, which aligns with the prior research, such as Baca & Zhushi, 2024; Sharma et al., 2022; Gan et al., Roh et al., 2023; and so on. Sharma et al. (2022) revealed that supportive infrastructure like reliable internet, easily accessible tutorials or training resources and timely client support were playing a significant role in shaping user attitude toward new technologies. Therefore, when UTAR students perceive that the necessary resources, technical support and platform assistance are available, they are more confident and inclined to use the AI investment instruments for their trading activities.

On the other hand, the result shows that Social Influence (SI) does not significantly affect the attitude of UTAR students in adopting AI investment tools for their trading strategies, rejecting H4 (SI→ATT). This is contrary to past research, such as Chung et al., 2017; Yeh et al., 2022; Fang et al., 2025; Papathomas et al., 2025, etc. This indicates that UTAR students rely more on their personal perceptions and evaluations rather than social recommendations like friends, family or social norms (Papathomas et al., 2025) when dealing with financial decisions. In other words, the UTAR students are more preferring to make the decision independently when it comes to AI-based investment tools.

Beyond this, the present study also displays that Prive Value (P) has a significantly positive impact on UTAR students' intention to adopt AI tools in investment strategies, supporting H5 (P→BI). This finding is consistent with earlier studies, which show users are more probably to apply financial technologies like robo-advisors when they observe that the advantages outweigh the related expenses. For example, Nainggolan and Handayani (2023) highlighted that users will consider transaction fees when selecting AI equipment. Meanwhile, they are more prefer the platforms that offer lower costs even when the superior may have a better interface design. Similarly, Amnas et al. (2023) reveal that when people believe that Fintech has cost-effective and obvious advantages of the services provided, they naturally integrate AI tools in their investment strategies. Hence, this study, which aligns with the past literature, confirms that UTAR students are more willing to use the AI instruments when trading or making investment decisions if they think the benefits and performance advantages exceed the financial cost associated with the acceptance of AI tools.

Plus, H6 of this study is supported (P→BI), where Habit (HA) was found to significantly influence BI, even though its effect was smaller compared to other predictors. This result supports the earlier research, like Amnas et al. (2023) reported that users often develop routines because digital financial systems are easily accessible and convenient, making them a natural choice for financial activities. This supported that the UTAR students who frequently use digital or AI-related tools show a higher intention to adopt AI investment instruments. Moreover, the experienced students tend to rely on robotic investment tools as they are now a regular part of their investment process (Zhafira et al., 2025).

In addition, the current study also found that Hedonic Motivation (HM) has a significantly positive effect on BI, which is in line with past literature. H7 in the present research is supported (HM→BI). The innovative, interactive and advanced features of AI tools can create a favourable emotional response, which improves openness towards the new technology adoption (Du et al., 2025) among the UTAR students. Likewise, Al-Okaily et al. (2025) further demonstrated that individuals who lack confidence in their own skills or financial knowledge often felt more at ease with AI technologies, boosting their emotional experiences. In this study, since the participants might not have the knowledge related to investment, they intend to use the AI tools. Additionally, young adults today (including UTAR students) experience greater enjoyment and engagement when using AI-powered platforms (Papathomas et al., 2025), since they grew up with digital technologies. Therefore, the findings state that enjoyment and emotional satisfaction positively shape UTAR students' intention to adopt AI tools.

Apart from that, Attitude (ATT) was found to have a strong and significant effect on BI, supporting H8 (ATT→BI). This result is consistent with Yeh et al. (2022); Belanche et al. (2019); and Noreen et al. (2023), all of which emphasised that individuals with positive attitudes towards AI technologies are more inclined to adopt them. Furthermore, Manrai and Gupta (2022) study also noted that when investors believe AI tools such as robo-advisors are useful and reliable, they may create a positive attitude that strongly translates into adoption intention. Similar to the present study, UTAR students who have a positive attitude have encouraged a robust intention to apply them. Meanwhile, most of the young generations, like

UTAR students, have a positive attitude as they have grown up with digital tools.

For the Gender (GNDR), the result displays that it has no significant impact on the BI of the UTAR students to using the AI instruments. This result is contrary to the prior study (e.g. Kuo et al., 2009; Schermerhorn et al., 2008). Meaning to say, male and female students had comparatively identical opinions and plans about the AI investment tools.

4.5 Conclusion

Overall, Chapter 4 presented the analyses of the survey data collected from 210 UTAR students, covering demographic analysis, awareness of AI investment tool, descriptive statistics, diagnostic tests and regression analyses. The demographic results show that most of the respondents were female, aged between 21 to 23 years old, and Buddhist. While they are also mainly from undergraduate students that from the Faculty of Accountancy and Management (FAM). Most of the students have limited experience with AI tools, and the platforms that they are familiar with, as well as widely used, are the Moomoo platform. The result also indicates that UTAR students usually have a positive perception towards AI investment tools, with a high level of usefulness, attitude and intention to use.

Besides, the diagnostic test showed that the regression model has met the assumption of SPSS. Both regression models were statistically significant and demonstrated strong explanatory power. In the Model 1, Perceived Usefulness, Facilitating Conditions significantly influenced Attitude, while Perceived Ease of Use and Social Influence were not supported. In Model 2, excluding the Gender, the other four predictors (including Price Value, Habit, Hedonic Motivation and Attitude) had a significant impact on Behavioral Intention.

CHAPTER 5: CONCLUSION

5.0 Introduction

This chapter summarises the major findings of the statistical analyses in Chapter 4. Then, it was followed by the discussion of the managerial implications of the study to highlight how this research can contribute to the real-world context, like a Fintech services provider or government initiatives. On the other hand, the limitations that were encountered during the study are acknowledged to guide future improvements and provide transparency. Therefore, this chapter also suggests several recommendations for future research based on the limitations.

5.1 Summary of Statistical Analyses and Major Findings

In summary, this study aimed to examine the factors influencing UTAR students' behavioural intention to adopt the AI tools in their investment strategies. According to this, a survey questionnaire was distributed, and a total of 210 valid responses were collected and analysed using descriptive statistics, reliability test, and multiple regression analysis using SPSS to test the proposed hypothesis.

The result revealed that some independent variables had statistically significant positive effects on Behavioural Intention (BI) to adopt the AI-based investment tool among UTAR students, including Perceived Usefulness (PU), Facilitating Condition (FC), Price Value (P), Habit (HA), and Hedonic Motivations (HM), and Attitude (ATT). In contrast, the Perceived Ease of Use (PEOU), Social Influences (SI) and Gender (GNDR) were not the important determinants to forecast the intention of UTAR students to utilise the AI-based investment tools. In simple words, UTAR students prioritise more the financial, useful, dependable advantages, enjoyment, and pre-existing habits, and enough supportive infrastructure or services.

On top of that, among all the predictors, Attitude (ATT) emerged as the strongest factor of BI, highlighting that the overall perception and evaluation of AI-powered investment tools play a central role in shaping their adoption intention.

Based on the findings, it can be concluded that almost all the hypotheses were supported, except the effect of PEOU (H2), SI (H4), and GENR (H9). Therefore, this study provides a clear summary of the statistical results and emphasises the main factor influencing both students' attitudes and behavioral intention to adopt the AI-based investment tools, thereby fulfilling the research objectives:

iii. To investigate the factors that influence UTAR students' attitudes towards AI-driven investment tools
iv. To examine the factors that shape UTAR students' behavioral intention to adopt AI-based investment tools.

Table 5.1: Summary of the findings

No.	Hypothesis	Findings
H1	To examine the influence of **perceived usefulness** on students' attitudes to use AI tools in investment strategies;	Supported
H2	To analyse the effect of **perceived ease of use** on the attitude towards AI-driven investment tools	Not Supported
H3	To investigate the impact of **facilitating conditions** on the attitude of students towards adopting AI investment tools	Supported
H4	To evaluate the role of **social influence** in shaping students' attitudes toward AI tools for investment	Not Supported
H5	To determine the effect of **price value** on students' behavioral intention toward AI-driven investment tools	Supported
H6	To assess how **habit** influences students' intention of AI investment tools	Supported
H7	To measure the effect of **hedonic motivation** on students' behavioral intention to adopt AI-driven tools for investment	Supported
H8	To test how the **attitude** influences students' behavioral intention to adopt AI investment tools	Supported
H9	To explore the influence of **demographic factors** (gender) on students' intention to use AI investment tools	Not Supported

Source: Designed for this study

5.2 Implication of the Study

Referring to the result of this study, some of the managerial implications can be drawn for the Fintech service providers and the government to guarantee that AI-powered investment tools are attractive to Malaysian investors, particularly young investors. First of all, the findings found that the availability of a reliable, dependable and efficient tool or platform will enhance the willingness of the UTAR students to use the AI-based investment tools. From here, it suggests that fintech service providers should make sure their platform or tools design is not only advanced and intelligent (Alwakid et al., 2025) but also needs to ensure that it is user-friendly (Park et al., 2024). For instance, they can provide clear instructions and simplified navigation features to help users adopt the system without objection.

Other than that, fintech service providers or the government also require providing adequate necessary infrastructure and resources to support the adoption, especially in rural areas. This includes improving internet accessibility, promoting the digital literacy project, and providing access to compatible devices like smartphones and laptops (Amnas et al., 2023). Most of the rural areas have limited access to financial services, leading to financial illiteracy (NexNews Network, 2025). Therefore, this kind of factor should be regarded as important by both service providers and the government to ensure a successful adoption and implementation of AI-based investment tools.

Next, financial considerations, such as transaction fees, remain an important factor for young investors. Since investor often prioritises the financial advantages, service providers must only offer fair prices (Fahruri et al. (2025), avoid unstated costs, and produce a product that is always time-saving (Du et al., 2025) to increase the willingness to adopt among the young investors. Also, cultivating routine use is essential for fostering habitual adoption of AI-based tools. For example, fintech services providers can create AI investment products or goods that easily adapt to users' current financial routines, such as linking them to popular banking or trading applications. At the same time, they can also offer the training program and tutorials for better understanding. This way can help the young investor incorporate AI tools into their daily routines.

Plus, enhancing the enjoyment and engagement is also quite significant to strengthen intention among young investors. For instance, the fintech services providers can incorporate the advanced features such as gamified components, dynamic dashboards and eye-catching interface design (Al-Okaily et al., 2025). By providing this, the user will more enjoyable or feel fun when using their AI tools or platform for trading, ultimately increasing the desirability of adoption. Additionally, positive user attitudes are also the key determinant for the success of the production of AI-based investment tools. In order to build confidence among users to the products, the fintech services providers must have the ability to solve the users' doubts (Belanche et al., 2019). In this way, it can not only boost the user's confidence but also motivate a continuing usability.

5.3 Limitations of the Study

Although the current study provides a useful insight, there are several limitations that should be acknowledged. Firstly, a total of 210 UTAR students have been collected in this study may not fully represent the broader population of young Malaysian investors. Otherwise, this study, which is mainly focused on UTAR students, can restrict the diversity of the perspective and limit the applicability of the findings to other demographic groups, like non-students and working adults. Beyond this, the targeted location of this study, which mainly focuses on Universiti Tunku Abdul Rahman, reflects a small geographical and institutional context. Hence, this result might not represent the opinions of students from other universities. Lastly, the study also did not examine the influence of the security, trust and privacy concern- the factor that is widely recognised as critical in the adoption of new technologies. The absence of these variables limits the explanatory power of the model. It may also overlook the risk-related considerations that might decrease the young investor's intention to adopt.

5.4 Recommendations for Future Research

Based on the limitations that have been identified, some recommendations are proposed to guide future research in understanding the adoption of AI-driven tools in Malaysia. Since the limitations of the sample size in present study, future studies should aim to collect data from a larger sample (>300 respondents) to improve the robustness of the findings. This is because the greater the sample size, the greater the accuracy of the representation of young investors' attitudes and behavoiral intention towards AI-powered investment tools. Furthermore, researchers are encouraged to extend the study beyond the young investor by involving other demographic groups, like working adults and retirees. This can provide a broader and more accurate perspective of Malaysian investors on how different age cohorts perceive and adopt the tools.

Besides, future studies can also expand the responses to the foreign country to enable a cross-cultural comparison. Meaning to say, the researchers can investigate the differences and similarities between Malaysian investors and those from other countries by this approach. This method not only provides a better understanding of where Malaysian investors stand in relation to global trends and behavioral patterns but also helps the fintech services providers to adjust their business planning, especially for those aimed at foreign users. The last recommendation for the subsequent research is integration with the other theories related to security, trust and privacy, like the Cognitive Trust Model. Covering these factors may improve the explanatory power of the research model and offer a deeper perspective into potential barriers to adoption.

5.5 Conclusion

Overall, this study has successfully examined the factors that influence the UTAR students' attitudes and behavioral intention to use the AI-driven investment tools based on the hybrid TAM-UTAUT2 framework, leading to the achievement of all objectives of this study. Meanwhile, it also provides a meaningful and useful managerial guidance for Fintech services providers, educational institutions and the government to enhance the adoption of AI tools among Malaysian investors, particularly young investors. Despite this, the present study is still limited by sample size, the respondents' group, geographical coverage and exclusion of some significant factors. It is recommended that future research address these limitations by expanding the sample size or targeted group, conducting cross-cultural comparison, and incorporating with other relevant theoretical frameworks. In short, this study can contribute as a foundation for future research and practical application in enhancing digital financial technology in Malaysia.

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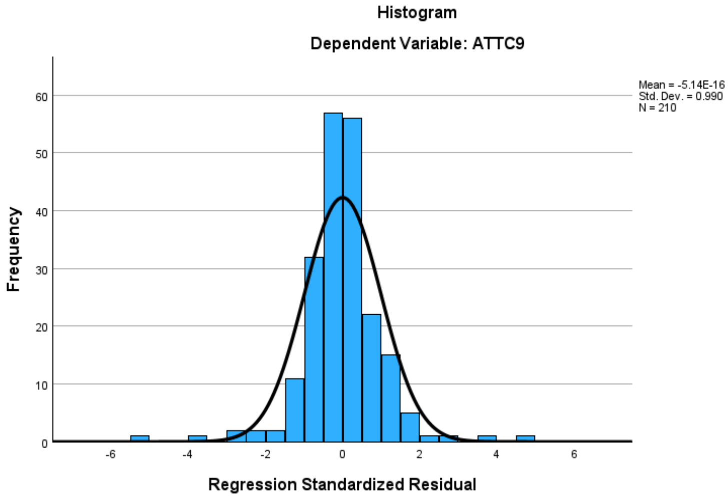
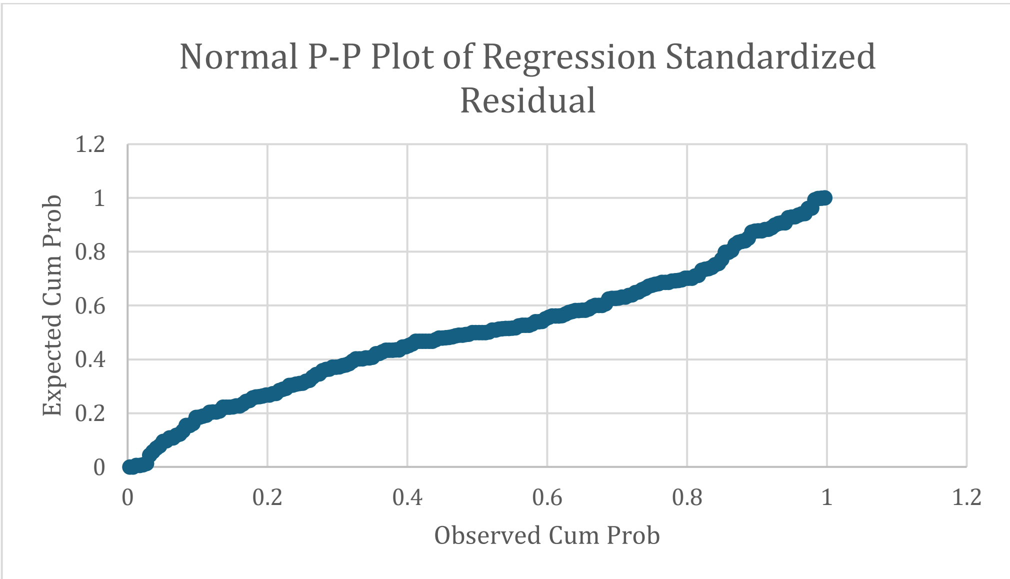
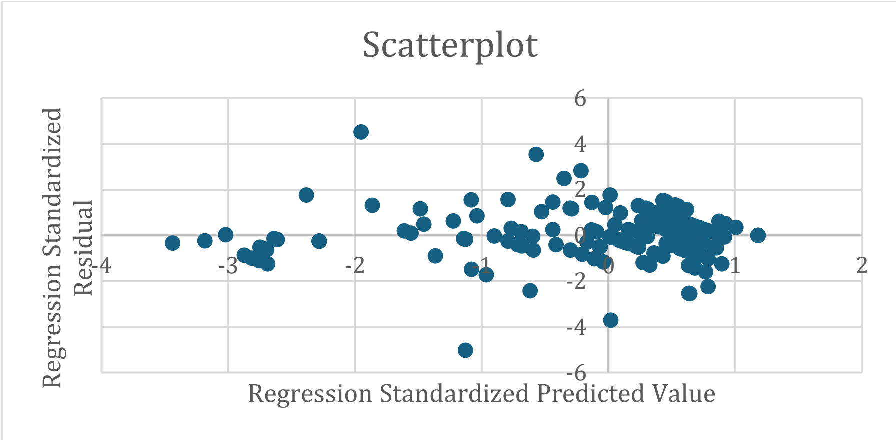
APPENDICES



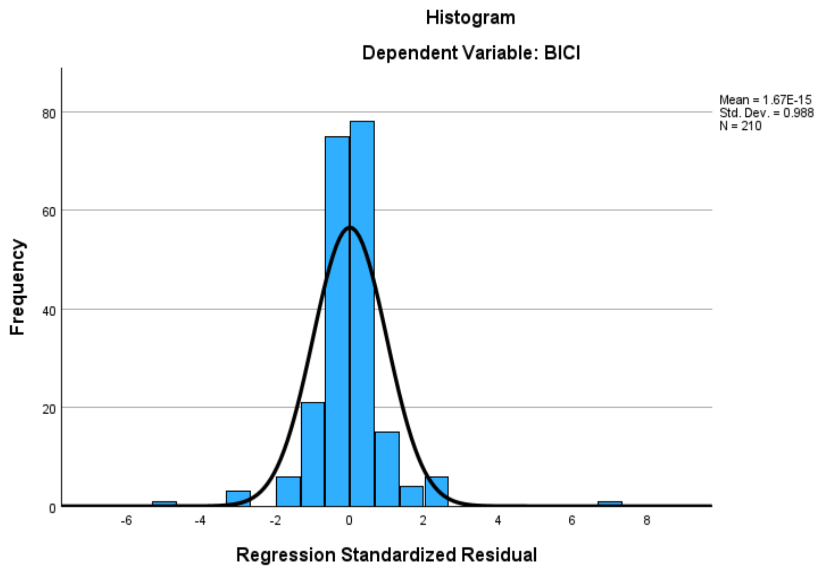
Appendix 1: Testing for the normality of residuals for Model 1



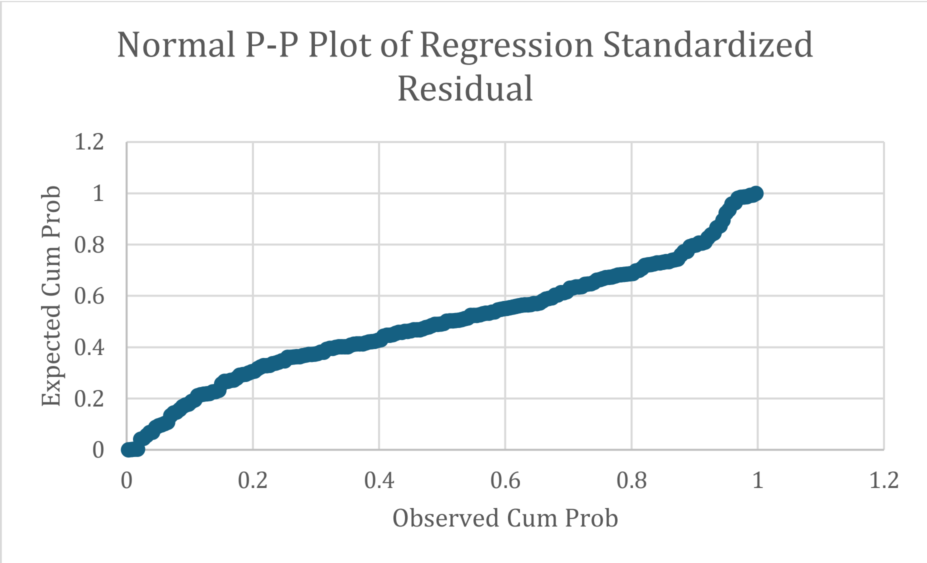
Appendix 2: A P-Plot of the Residual for Model 1



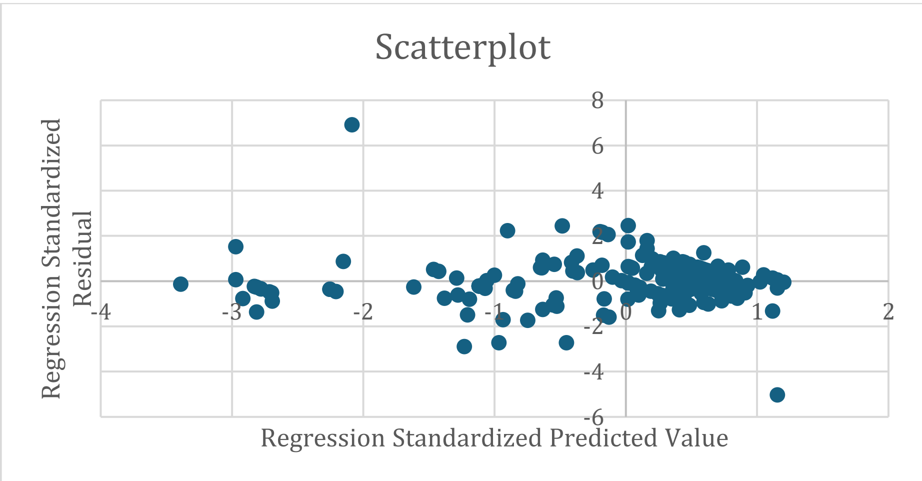
Appendix 3: Scatterplot of Standardised Residuals based on predicted Grades for Model 1



Appendix 4: Testing for the normality of residuals for Model 2



Appendix 5: A P-Plot of the Residuals for Model 2



Appendix 6: Scatterplot of Standardised Residuals based on predicted Grades for Model 2

Appendix 7: Questionnaire

Acceptance of AI Tools in Investment Strategies: Evidence from Universiti Tunku Abdul Rahman (UTAR).

Survey Questionnaire

Dear Respondents,

I am currently pursuing my Bachelor of Finance (Financial Technology) with Honours at Universiti Tunku Abdul Rahman (UTAR). I am conducting research on University Students' Acceptance of AI Tools in Investment Strategies: Evidence from Universiti Tunku Abdul Rahman (UTAR). The aim of this study is to gain new insights into the factors contributing to the intention of UTAR students to use Artificial Intelligence (AI) Tools in their investment strategies. This study is approved by the UTAR Scientific and Ethical Review Committee, Ref No.: XXXX.

I will be very grateful if you can spare 15 minutes of your valuable time to answer the survey questionnaires. Please answer all the questions, as I greatly value your thoughts and beliefs. Participants' names, emails, institutions, and all answers during data collection will be treated with absolute confidentiality.

Informed Consent:

- I voluntarily agreed to participate in this research on [University Students' Acceptance of AI Tools in Investment Strategies: Evidence from Universiti Tunku Abdul Rahman in University Tunku Abdul Rahman (UTAR).
- I understand that even if I agree to participate now, I can withdraw at any point of time or refuse to answer any question without consequences of any kind.
- I understand that participation involves filling in questions regarding my sociodemographic information, awareness about the AI, behavioral intention, perceived usefulness, perceived ease of use, price, habit, social influence, hedonic motivation, facilitating condition, and attitude.
- I understand that I will not benefit directly from participating in this research.
- I understand that all information provided for this research will be treated confidentially.
- I understand that I am free to contact the people involved in the research to seek further clarification and information.

By clicking the link below, you hereby consent to participate in this research.

Helen Tee Xin Ye

23UKB05345

Signed by Supervisor:

<u>Section A: Respondent's Background</u>

A1. Gender

1. Male 2. Female

A2. Age Group:

1. 18-20 2. 21-23 3.24-26 4. 27-29 5. 30 and above

A3. Faculty, Institutes and Centres

1. M. Kandiah, Faculty of Medicine and Health Sciences (Sungai Long Campus)
2. Lee Kong Chian Faculty of Engineering and Science
3. Faculty of Engineering and Green Technology
4. Faculty of Information and Communication Technology
5. Faculty of Science
6. Faculty of Accountancy and Management (Sungai Long Campus)
7. Teh Hong Piow Faculty of Business and Finance (Kampar Campus)
8. Faculty of Arts and Social Science (Kampar Campus)
9. Faculty of Creative Industries
10. Institute of Postgraduate Studies & Research
11. Institute of Chinese Studies
12. Institute of Management and Leadership Development
13. Centre for Foundation Studies (Kampar Campus)
14. Centre for Foundation Studies (Sungai Long Campus)

15. Centre for Extension Education

16. Centre for Corporate and Community Development

A4. Ethical Group

1. Malays 2. Chinese

3. Indians 4. Others (please specify): _______

A5: Religion

1. Muslim 2. Buddha 3. Hindu

4. Kristian 5. Others (please specify): _____

A6: Education Level

1. Foundation 2. Undergraduate

3. Master’s Degree 4. Doctorate/PhD

A7. Previous investment experience

0. None 1. Less than 1 year 2. 1-3 years

3. 3-5 years 4. 5-10 years 5. More than 10 years

Section B: Awareness about the AI tools in Investment Strategies

Definition of AI: A particular computer systems or machine that possess some of the characteristics of the human brain. For example, the ability to explain and produce language in a way that sounds human, recognize or generate images, overcome problems, and study from data given to it.

B1. Which types of AI-powered investment and research tools (AI investment tools) for the stock market are you familiar with or have knowledge of? (Can select more than 1)

0. Do not use
1. Moomoo Malaysia – Moomoo AI
2. AI StockMaster (via MalaysiaStock.biz)
3. Wahed Invest
4. Daloopa – Automates structuring of financial disclosures (SEC filings, earnings) into usable datasets.
5. FinChat.io – Conversational AI for financial data, transcripts, and research summaries.
6. AlphaSense – AI-powered search engine for filings, transcripts, and analyst reports.
7. StockInsights.ai – Tracks filings, news, and company updates with AI-generated summaries.
8. TipRanks – AI-driven analyst rankings, insider trading analysis, and Smart Scores for stocks.
9. Visualping – Monitors corporate and regulatory webpages for real-time updates.
10. Dataminr – Real-time AI alerts on breaking market events and sentiment.
11. Kavout (Kai Score, InvestGPT) – AI stock scoring and predictive analytics.
12. Tickeron – AI-based trading signals, forecasts, and pattern recognition.
13. Danelfin – AI stock ranking and trade ideas for U.S. and European markets.
14. Forecaster AI Agent – 24/7 LLM-powered assistant integrated in Forecaster Terminal.

15. Bloomberg Terminal (AI-enhanced) – AI tools built into Bloomberg for faster analyst workflow.
16. Sentieo – AI-driven financial research, document search, and data visualization.
17. FinWorld – Open-source financial AI platform for data ingestion, analysis, and deployment.
18. FinRobot – LLM-based research agent that mimics human analyst reasoning.
19. MarketSenseAI – AI-agent for holistic analysis (news, fundamentals, macro data).
20. Zacks Research Wizard (AI-enhanced) – Stock screening and backtesting tool with AI-driven enhancements.
21. Eikon (Refinitiv, LSEG) – AI-powered market data and analytics platform.
22. Other, please specify _______________

B2. Which types of AI-powered investment and research tools for the stock market have you used? (Can select more than 1)

0. Do not use
1. Moomoo Malaysia – Moomoo AI
2. AI StockMaster (via MalaysiaStock.biz)
3. Wahed Invest
4. Daloopa – Automates structuring of financial disclosures (SEC filings, earnings) into usable datasets.
5. FinChat.io – Conversational AI for financial data, transcripts, and research summaries.
6. AlphaSense – AI-powered search engine for filings, transcripts, and analyst reports.
7. StockInsights.ai – Tracks filings, news, and company updates with AI-generated summaries.
8. TipRanks – AI-driven analyst rankings, insider trading analysis, and Smart Scores for stocks.
9. Visualping – Monitors corporate and regulatory webpages for real-time updates.

10. Dataminr – Real-time AI alerts on breaking market events and sentiment.
11. Kavout (Kai Score, InvestGPT) – AI stock scoring and predictive analytics.
12. Tickeron – AI-based trading signals, forecasts, and pattern recognition.
13. Danelfin – AI stock ranking and trade ideas for U.S. and European markets.
14. Forecaster AI Agent – 24/7 LLM-powered assistant integrated in Forecaster Terminal.
15. Bloomberg Terminal (AI-enhanced) – AI tools built into Bloomberg for faster analyst workflow.
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17. FinWorld – Open-source financial AI platform for data ingestion, analysis, and deployment.
18. FinRobot – LLM-based research agent that mimics human analyst reasoning.
19. MarketSenseAI – AI-agent for holistic analysis (news, fundamentals, macro data).
20. Zacks Research Wizard (AI-enhanced) – Stock screening and backtesting tool with AI-driven enhancements.
21. Eikon (Refinitiv, LSEG) – AI-powered market data and analytics platform.
22. Other, please specify _______________

B3. Investment Experience using AI-powered investment and research tools for the stock market

0. None   1. Less than 1 year   , 2. 1-3 years

3. 3-5 years   4. 5-10 years   5. More than 10 years

Section C: Variables in the Framework Model

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
A	Behavioural Intention					
1.	I intend to keep using AI investment tools for making sustainable investment decisions.	1	2	3	4	5
2.	I would recommend others to use AI investment tools for making sustainable investments.	1	2	3	4	5
3.	I think I am going to use AI technology in future trading.	1	2	3	4	5
4.	I have a positive impression of AI-based investment applications and platforms overall.	1	2	3	4	5
5.	Utilizing the AI-based application and platforms appears to be a favourable decision.	1	2	3	4	5
6.	The use of AI technology is a good concept.	1	2	3	4	5
7.	It is a clever choice to use AI-based investment tools over other traditional services.	1	2	3	4	5
B	Perceived Usefulness					
8.	It is a clever choice to use AI-based investment tools over other traditional services.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
9.	The AI-based investment platform provides me with valuable information about investment market opportunities.	1	2	3	4	5
10.	The AI tools improved my skills in conducting investment transactions.	1	2	3	4	5
11.	AI investment tools have empowered us to make faster and more data-driven decisions.	1	2	3	4	5
12.	AI investment tools have allowed us to make more informed and timely investment decisions.	1	2	3	4	5
13.	AI investment tools allowed us to improve our risk management and identify potential risks that may be overlooked by human analysts.	1	2	3	4	5
14.	AI investment tools have enabled us to identify undervalued assets that may not be easily detectable using traditional methods.	1	2	3	4	5
15.	The AI investment tools is helpful in aligning my investment strategy with sustainability.	1	2	3	4	5
C	Perceived Ease of Use					
16.	AI technology would be easy for me to learn.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
17.	My interaction with AI investment tools does not need me to think too much.	1	2	3	4	5
18.	AI technology use in my AI tasks completion is easy.	1	2	3	4	5
19.	Interaction using AI technology seems flexible	1	2	3	4	5
20.	I think I can master AI technology.	1	2	3	4	5
D	Price					
21.	AI-based trading application and platforms have helped us execute trades more efficiently and reduce transaction costs.	1	2	3	4	5
22.	The AI-based trading applications and platforms offered competitive investment prices for students	1	2	3	4	5
23.	The satisfaction with the benefits I received from using the AI tools is higher.	1	2	3	4	5
24.	The benefits provided by the AI investment tools encourage me to invest further.	1	2	3	4	5
25.	The value I receive from the AI investment tools justifies its cost.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
26.	At the current price, AI investment tools provide a good value.	1	2	3	4	5
E	Habit					
27.	Using AI tools has become a habit for me when trading.	1	2	3	4	5
28.	It has been natural for me to use AI investment tools.	1	2	3	4	5
29.	I am addicted to using the AI investment tools.	1	2	3	4	5
30.	I feel I need to use AI tools when trading.	1	2	3	4	5
F	Social Influence					
31.	When I see that AI investment tools are recommended to me based on the preferences of other users, I feel more confident in using them.	1	2	3	4	5
32.	I am influenced by the popularity of AI investment tools among other users when deciding whether to use them.	1	2	3	4	5
33.	AI investment tools are more appealing to me when I see that they have been endorsed or shared by friends or peers on social media.	1	2	3	4	5
34.	I utilised the AI-based investment trading	1	2	3	4	5

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
	applications and platforms to follow my peers.					
35.	Due to my lack of investment knowledge, I used an AI-based investment application and platforms when trading.	1	2	3	4	5
36.	My family thinks that using an AI-based investment platform is a good idea.	1	2	3	4	5
37.	Most of my friends would use AI investment tools for trading.	1	2	3	4	5
G	Hedonic Motivation					
38.	I derive satisfaction from discovering unique and personalized investment recommendations that enhance my trading experience.	1	2	3	4	5
39.	The AI tools in the investment applications and platforms make me happy with my investment choices.	1	2	3	4	5
40.	I believe that using Artificial Intelligence will be annoying.	1	2	3	4	5
41.	Using the AI investment tools is very entertaining.	1	2	3	4	5
H	Facilitating Condition					

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
42.	I possess the requisite resources to utilize the AI investment tools.	1	2	3	4	5
43.	I possess the necessary knowledge to make use of the AI-based investment application and platforms.	1	2	3	4	5
44.	If I face any challenges while using the AI-based investment application and platforms, I can seek assistance from others.	1	2	3	4	5
45.	AI-based investment platforms and applications are regularly updated and improved, making them more user-friendly for investment activities.	1	2	3	4	5
46.	AI-based investment platforms and applications offer clear instructions and guidance on how to effectively use their features for investment decisions.	1	2	3	4	5
I	**Attitude**					
47.	I have a positive impression of AI-based investment applications and platforms overall.	1	2	3	4	5
48.	Utilizing the AI-based application and platforms appears to be a favorable decision.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
49.	The use of AI technology is a good concept.	1	2	3	4	5
50.	It is a clever choice to use AI-based investment tools over other traditional services.	1	2	3	4	5

Thank you