Antecedents Of University Students' Behavioral Intention to Use Artificial Intelligence-Based Investment Tools

BY

YOONG SHI QI

A research project submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF FINANCE (FINANCIAL TECHNOLOGY) WITH HONOURS

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Declaration

We hereby declare that:

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

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

(3) The word count of this research report is _____24292 words_____.

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List Of Abbreviations

AI – Artificial Intelligence

ATT – Attitude Toward Using

AW – Awareness of Service

BI – Behavioral Intention

CI – Confidence

FYP – Final Year Project

MLR – Multiple Linear Regression

PEOU – Perceived Ease of Use

PR – Perceived Risk

PU – Perceived Usefulness

SE – Smartphone Self-Efficacy

SI – Social Influence

SPSS – Statistical Package for the Social Sciences

TAM – Technology Acceptance Model

TRA – Theory of Reasoned Action

UTAR – Universiti Tunku Abdul Rahman

Preface

This research project was carried out as part of the requirements for the Bachelor of Finance (Financial Technology) with Honours programme at Universiti Tunku Abdul Rahman (UTAR).

The study explores the antecedents influencing UTAR students' acceptance of Artificial Intelligence (AI)-based investment tools, focusing on key constructs such as perceived usefulness, perceived ease of use, trust, perceived risk, and social influence.

The preparation of this report has enhanced my academic research skills and deepened my understanding of technology adoption in the financial sector. It is my sincere hope that the findings will provide useful insights for future researchers, fintech developers, and policymakers in Malaysia.

Abstract

The financial industry is experiencing a surge in AI technology usage. This technology is impacting how many individuals make decisions regarding their investments and how they invest through automation, using what are referred to as "Robo-Advisors" and Automated Trading Platforms. The question is whether younger people (university attendees) will adopt these methods of investing. Thus, the purpose of this study is to understand what influences university students' intentions toward utilizing AI investment methods by integrating the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA) within an empirical research framework. Specifically, this research project will be examining the influence that various variables have on students' attitudes towards investing using AI: (1) Perceived Usefulness; (2) Perceived Ease of Use; (3) Trust; (4) Perceived Risk; (5) Social Influence; (6) Awareness of the Service; (7) Confidence; (8) Smartphone Self-Efficacy; and (9) Internet Connection Quality. Using a Convenience Sampling Method, the researchers gathered Survey Data from a sample of UTAR students and conducted the data analysis using Quantitative Technique(s). This study provides an insight into the technological, psychological, and social aspects of students' Acceptability/Acceptance of using AI investment tools and contributes to the growing body of Literature around Technology Adoption, along with providing some practical applications for the Financial Technology Sector to use in their Marketing strategies when promoting AI Investment Services to young investors.

Chapter 1 Introduction

1.0 Research Background

As the field of Artificial Intelligence matures rapidly, it has created more and better products such as robo-advisors, algorithmic trading systems, and AI-based portfolio management for the Financial Industry. Because these products use data-based techniques and work faster than we do, they enable us to make investment decisions more efficiently, at lower service costs. However, while the availability of AI products continues to expand, investors vary in their willingness to use these tools; in part because of the level of trust associated with these products and how much financial risk they pose.

Moreover, according to Grand View Research (2024), the projected growth rate of the global AI market over the period 2024 - 2030 is estimated to be a compounded annual growth rate (CAGR) of 35.9%, with an increase of USD 279.22 billion in 2024 to USD 1,811.75 billion in 2030. Additionally, there has been an exponential increase in the number of organizations that are using AI; McKinsey reported that 78 percent of organizations had implemented AI in at least one business function by 2025, compared to only 55 percent in 2024.

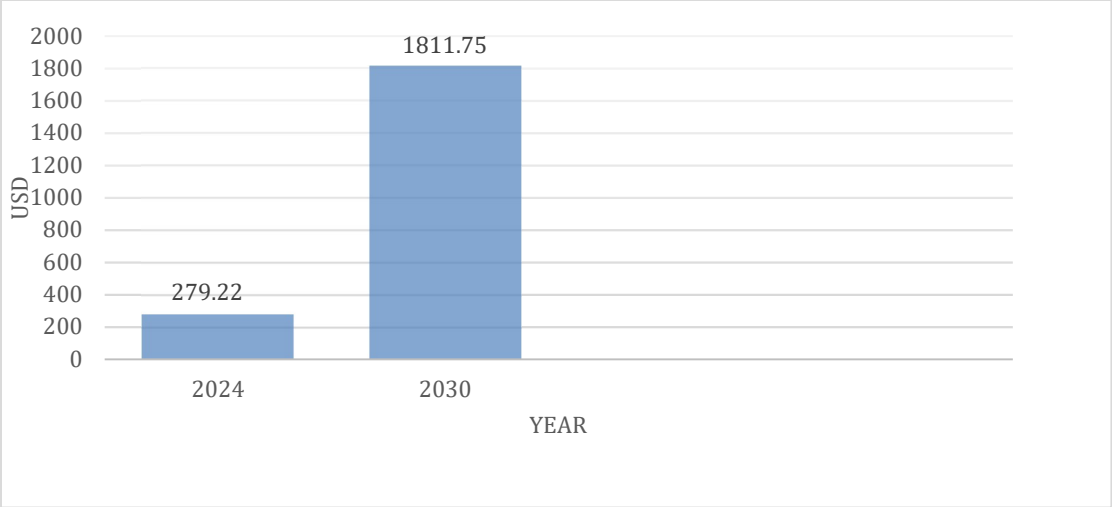


Table 1.1 Global AI Market Growth (Grand View Research, 2024)

Earlier researches regarding the use of AI in various service areas primarily concentrated upon service environments where AI is being used including customer service through chatbots, self-service kiosks and recommendation systems Wirtz et al. (2018) point out, that according to previous research, three areas of concern that customers have related to AI when using it for customer service are their trust in the AI system, privacy concerns, and their feeling of discomfort, which many have described as creepiness. These same three areas of concern are just as critical to finance because the AI systems utilized within the Finance industry have been utilized to a greater extent to replace the user from an active decision-making standpoint, rather than functioning simply as a manner of supporting or assisting users.

Another important concept regarding algorithm aversion is how individuals can become discouraged or drop out of using an AI system once they see a minor error occur. This is especially relevant in financial contexts, as an investor may hesitate to use an algorithm-based solution even when it offers higher returns than a human managed fund simply because of one mistake previously made by the algorithm. However, the research on algorithm aversion has yielded mixed results. The findings by Filiz et al. (2022) were not indicative of high levels of algorithm aversion in the context of making investment decisions, as the focus of the subjects was primarily on the returns of each fund and not on the type of fund manager. In addition, this study

suggested that subjects struggled to distinguish whether the performance of the human manager was due to skill or luck, which indicates some potential issues with confidence and trust in the outputs of AI systems.

The findings of the study show that further research is necessary to determine what factors influence investors' desire to invest in AI. Investors tend to make many high-risk investment decisions, which may affect how they perceive risk and how they view value and trust as a whole. The TAM (Technology Acceptance Model) explains technology acceptance based on the perceived usefulness and perceived ease of use. But by looking solely at these two main factors, we may still be missing important pieces of information about how investors make their AI investment decisions. It is also likely that other factors, such as trust and perceived risk, play a role in how investors respond to the performance of algorithms in a high-risk decision-making environment like investing. In addition, few empirical studies have been conducted about Malaysia, particularly about young users like university students, who represent a new segment of digitally savvy investors.

These inconsistent cues from AI aversion support a growing need to investigate the antecedents of the acceptance of AI among investors, a group that makes high-stakes decisions and likely evaluates risk, trust, and perceived value differently than consumers at large. Whereas the Technology Acceptance Model (TAM) has offered explanations regarding technology adoption based on topics of perceived usefulness and ease of use, emerging findings highlight the insufficiency of those two aspects alone to explain the dynamics of financial decision-making in an AI context. There is increasing recognition of concerns such as trust, perceived risk, and algorithm aversion, offering an opportunity to continue and extend TAM with other psychologically based antecedents that are pertinent to high-stakes decision-making situations like investing. Moreover, there are few (to no) empirical studies in the Malaysian context, notably with youth populations such as university students, as this demographic embodies a new generation of digitally literate investors. This study aims to bridge these identified

gaps by understanding how UTAR students perceive and accept AI in relation to financial decision-making.

1.1 Problem Statement

The use of Artificial Intelligence (AI) and its applications in financial management has changed the way consumers and companies approach budgeting, investing, and financial planning. AI-driven technologies, such as automated budget planners or robot-advisors, apply machine-learning methods to assess historical data, forecast future expenses, and provide tailored financial recommendations (Sharma & Garg, 2023). In theory, integrating AI can improve the quality of financial decision-making practices by improving efficiency, increasing objectivity, and making financial advice more accessible. Yet, for all the benefits mentioned, acceptance and adoption of AI applications still vary across demographic groups and situations (Filiz et al., 2022; Verdickt & Stradi, 2025). Prior research has found inconsistent evidence of how much users trust and depend on AI for high-stakes financial decisions. These findings bring several important questions about how investor behavior towards AI is determined and warrant additional research to enhance our understanding through the application of theory and empirical research.

To date, much of the research around AI acceptance has taken place in customer service contexts (Wirtz et al., 2018) and has focused on issues of trust, privacy, and discomfort using computers. Investors operate in circumstances where stakes are high in terms of decision making, are called to consider more complex information, and are subject to even more financial risks related to their decision making. As such, the antecedents of AI acceptance (in the form of perceived trust, perceived risk, algorithm aversion, and system transparency) may have different implications for investors than they would have for the expected technology user.

Research findings are mixed. For example, Filiz et al. (2022) reported no algorithm aversion in financial decision making. In their study, investor-functional participants did not prefer human fund manager nor did they lose trust in the AI systems after AI made errors, suggesting outcome performance supersedes aversion. On the other hand, Verdickt and Stradi (2025) contradicted this and showed algorithm aversion continued for investors especially when AI parameters and predictions were opaque or had too much complexity. They also emphasized demographic characteristics such as age and AI literacy were factors that moderated acceptance.

Furthermore, limited research exists in the Malaysian context, especially among young investors. While Malaysia's fintech adoption is rising, there is a lack of targeted studies that explore university students' attitudes toward AI-based financial systems—even though students represent the next generation of digitally fluent investors. According to Yi et al. (2023), trust and usability significantly affect robot-advisor adoption among Malaysian millennials, but perceived risk may have a weaker impact, indicating local behavioral differences compared to global patterns.

These inconsistencies contribute to a considerable gap in the research. The prediction predicting investor acceptance of AI have not yet been sufficiently investigated in non-Western contexts focused on youth and by using an integrated behavioral model such as the Technology Acceptance Model (TAM). Recent work has emphasized the increasing role of attitudes and emotional factors in influencing outcomes in financial decision-making (e.g., trust, perceived risk, psychological comfort, algorithm aversion), which may even supersede beliefs regarding perceived usefulness and perceived ease of use (Sabir et al., 2023). Taking into consideration these developments and the findings by Chung et al. (2023), which demonstrate how investor acceptance of AI varies based on levels of uncertainty, this study poses the following central research question.

How are trust, perceived risk, psychological comfort, and the main constructs of the Technology Acceptance Model (TAM), namely perceived usefulness and

perceived ease of use, related to the behavioral intention to use AI-based investment tools among Malaysian students at UTAR, and how do these relationships reflect the specific attitudinal and contextual factors emphasized in the existing literature, particularly in non-Western, youth-driven fintech contexts?

In addressing this question, this study's overall aim is to provide a thorough examination of the different psychological, technological, and social elements that affect university students in Malaysia's acceptance and the use of AI-based investment tool technology, specifically the students at University Tunku Abdul Rahman (UTAR). More specifically, the study will examine how Perceived Usefulness (PU) affects students' attitudes toward adoption, and how Perceived Ease of Use (PEOU) affects the willingness to use or adopt these technologies. The study will also consider the effects of Trust in AI concerning reliability, transparency, and fairness on adoption, as well as Social Influence in determining intention concerning peers, friends, family, and influencers. In addition, the study will analyze Perceived Risk regarding uncertainty, potential for financial loss, and privacy will have on social factors and individual factors of behavior. Lastly, demographic variables, such as age and gender, will be explored to moderate the relationship between Behavioral Intention and Actual Use of AI tools.

By achieving these objectives, this study will contribute to theory by broadening TAM in a non-Western context focused on youth and provide practical implications for fintech developers and policymakers in Malaysia that wish to understand how to initiate the greater rate of adoption of AI financial technologies.

1.2 Research Question

In this study, 12 research questions are posed to explore each of the 12 hypotheses which support the purpose of the research:

Main Research Questions: What are the antecedents that influence university students' behavioural intention to use Artificial Intelligence (AI)-based investment tools based on the integrated Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA)?

RQ1: How does a student's assessment of the value of AI in their investments impact their views towards its value for investment decisions?

RQ2: How does the student's assessment of the usefulness of using an AI investment tool compare to how UTAR students assess the level of usefulness of the AI investment tool?

RQ3: In what ways does the PEOU comparison of the AI investment tool impact the student's view towards AI in their investment decisions?

RQ4: What is the impact of student trust in an AI system on their views of AI for investment purposes?

RQ5:How does a student's assessment of AI for investment purposes impact their perception of risk?

RQ6:To what extent does social influence determine how students view AI for investment purposes?

RQ7: To what extent will the student's attitude towards AI in their investment decisions impact their behavioral intention to use AI investment tools?

RQ8: Are students aware of how services impact their assessment of AI for investment purposes?

RQ9: To what extent does the student's perception of their self-efficacy with smartphones impact their perception of the AI investment tool's PEOU?

RQ10: How does the quality of the student's internet connection and websites impact the student's perception of the PEOU of AI investment tools?

RQ11: How does the student's level of confidence impact their views towards AI in investment purposes?

1.3 Research Objectives

This study primarily aims to study the different psychological, technological, and social factors that influence university students in Malaysia, specifically University Tunku Abdul Rahman (UTAR) students, when considering whether to accept and adopt Artificial Intelligence (AI)-based investment tools. The study also aims to identify whether demographic factors like age and gender moderate the relationship between Behavioural Intention and Actual Usage of AI tools.

The key aims of the current research are to:

- To examine the antecedents that influence university students' behavioural intention to use Artificial Intelligence (AI)-based investment tools by

integrating the Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA).

The specific goals of this study are:

RO1: Evaluate how perceived usefulness influences student attitudes toward using AI in investing.

RO2: Evaluate how perceived ease of use impacts a student's views on the utility of an AI-based investment platform.

RO3: Evaluate how perceived ease of use impacts a student's attitude toward the use of AI in investing.

RO4: Evaluate how students' level of trust in AI influences their attitudes toward its use in investing.

RO5: Evaluate how students perceive risks associated with using AI in investing.

RO6: Evaluate how social influence impacts students' attitudes toward AI in investing.

RO7: Evaluate how a student's attitude toward using AI for investing will affect that student's behavior when using AI for investing.

RO8: Evaluate how students' awareness of AI-based investment services impacts their perceptions of usefulness.

RO9: Evaluate how students' confidence in their smartphone skills affects their perceived ease of use of an AI-based investment platform.

RO10: Evaluate how the quality of students' internet connections and websites affect the perceived ease of use of an AI-based investment platform.

RO11: Evaluate how students' level of confidence in their ability to use AI for investment decisions impacts their attitudes toward using AI for investing.

1.4 Significance of the study

This research has both theoretical and practical implications. Theoretically, this research contributes to the Technology Acceptance Model (TAM) by integrating components of the Theory of Reasoned Action (TRA) and including psychologically driven variables of trust, perceived risk, and social influence. The research responds to recent calls in the literature to develop more context-specific models of technology adoption in complicated, risky environments, such as financial decision-making. This study also develops the existing body of knowledge on acceptance in areas of financial technology (fintech) and artificial intelligence, especially among young people in emerging markets.

Practically, this research data provides actionable insights into making AI-based investment tools, such as robot-advisors and algorithmic platforms, more user-friendly and psychologically palatable for young investors looking for online tools to manage their personal finances. Knowing the behavioral intention factors of trust, perceived risk, and ease of use can assist fintech developers. Researchers, fintech

providers, and consumer educators can also use findings from the research to inform public efforts to promote AI technologies as tools to assist audience members in managing their personal finances. At the societal and policy level, the study supports Malaysia's national agenda to foster a digitally inclusive financial ecosystem. As university students represent the next generation of investors, identifying factors that enhance or hinder their acceptance of AI tools can inform targeted financial literacy programs and regulatory measures. The findings could be valuable to policymakers, educational institutions, and financial regulators seeking to shape a responsible, tech-enabled investment culture.

1.5 Outline of the study

This study is divided into five chapters. Chapter 1: Introduction revisits the research background, outlines the study problem, research questions, objectives and hypotheses and the significance of the study. It also outlines the study report structure. Chapter 2: Literature Review reviews relevant theories (Technology Acceptance Model [TAM], Theory of Reasoned Action [TRA], and Extended TAM) and the empirical literature related to perceived usefulness, perceived ease of use, trust, perceived risk, and social influence that informed the conceptual framework and hypotheses for the study. Chapter 3: Research Methodology describes the research design, sample selection, data collection methods, and instruments used in the study. It also describes the data analysis methods in using SmartPLS and identifies the ethical considerations. Chapter 4: Data Analysis and Findings reports the descriptive and inferential statistical analysis, which includes the measurement model and structural model assessments and testing the hypotheses. Finally, Chapter 5: Conclusion and Implications summarizes the key findings, discusses the study's implications for theory and practice, identifies limitations of the study, and makes suggestions for future research.

Chapter 2: Literature Review

2.0 Introduction of Literature Review

This chapter discusses relevant theories, concepts, and empirical studies that frame the research. The literature review presents the theoretical and conceptual research foundations from which to explore factors influencing student use of AI-based investment tools. This chapter presents the underlying frameworks from which the study is guided - the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA) that offer a theoretical basis to explain users' behavioral intentions toward the adoption of technology. To develop the literature review, key constructs were taken from the TAM and TRA models, as well as from the literature in constructs to be included - perceived usefulness, perceived ease of use, perceived risk, trust, confidence, social influence, awareness, self-efficacy, quality of internet connection, attitude, subjective norm, and behavioral intention.

Through evaluating previous studies in the literature review and synthesizing knowledge from established theories, the chapter identifies functional and psychological factors that either support or deter technology use. The literature review also identifies gaps in the literature and supports justification for the original variables and new variables to extend the research model. The literature review serves two purposes: provides a basis from which to derive a research hypothesis, and also provides further theoretical rationale for the study.

2.1 Introduction of model - Technology Acceptance Model (TAM) and Theory Of Reasoned Action (TRA)

The Technology Acceptance Model, or (TAM), was initially derived from the Theory of Reasoned Action (TRA). It has emerged as one of the most popular theories for understanding and predicting technology user acceptance. TRA explains and predicts user acceptance based on the user's attitude, beliefs, and values to establish behavioral intention, which is then foundational for TAM. Following the TRA, Davis (1989) introduced TAM to address a gap in the extant literature related to information technology systems, developing the idea that the acceptance and ultimate use of the technology is, in part, dependent on two major factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).

PU is defined as the degree to which a person believes that using a particular system would be beneficial for job performance or will result in other tangible benefits. PEOU, on the other hand, is described as the degree to which a person believes that interacting with the technology will be free of effort or complexity. TAM suggests that PU and PEOU, to be significant influences on a user's Attitude Towards Using (ATU) and ultimately Behavioral Intention to Use (BIU). BIU is helpful to, and often predicts, actual usage or adoption behavior. BIU, then, is an important component of the overall adoption process.

Although TAM has shown strong explanatory power from the outset, researchers have later acknowledged its shortcomings in explaining factors outside of technology adoption decisions. In reality, adoption behavior is rarely determined by internal perceptions and feelings of usefulness and ease of use, as many of the external

and even social and psychological factors at play in forming user attitudes and intentions are played emphasized as important (Alalwan et al., 2016).

For that matter, this study adopts an Extended TAM by considering additional constructs, including Social Influence, Self-Efficacy, Perceived Risk, Trust, and Convenience. As examples, Social Influence is how much a person's technological adoption opportunities or decisions is related to the actions or opinions of others and Self-Efficacy is a person's confidence in their ability to effectively use the technology (Abbad, 2023). Perceived Risk is uncertainty or potential negative outcomes and Trust which guides the user's confidence in the credibility of the technology developers and suppliers. Convenience refers to perceived reality about technologies ability to save time, energy, or resources.

Having considered the above constructs, an Extended TAM is a dimensional analysis of user adoption behavior that gives a deeper and more complex view of technology decisions are hybridized experiences of functional, social, and psychological practices.

2.2 Theory Of Perceived Usefulness

Perceived usefulness (PU) describes the extent to which one believes using a system will enhance their performance or decision-making outcomes. For instance, with AI-based investment tools, PU is represented by the investor's belief that AI will yield more astute financial insights, improve portfolio allocation, and save time and effort on financial analyses. Prior research indicates that the application of AI

technology in financial services has many obvious benefits, such as real-time risk analysis, predictive analytics, and automated portfolio management, and this can lead to a higher quality of investment decisions compared to traditional approaches. When investors experience these benefits, they often have a more favorable opinion about technology. There are studies that demonstrate the impact of PU on attitudes toward technology acceptance, especially in financial technology and robot-advisory services that report user acceptance is strongly influenced by perceived efficiency gains (Vilakshan, XIMB Journal of Management, 2024). Thus, it is anticipated that the higher the PU of an investor of AI-based investment tools, the more favorable their attitudes toward the use of AI will be.

2.2.1 Social Influence

Originating from the Theory of Reasoned Action's (TRA) formulation of subjective norms, Social Influence (SI) can be understood as the extent to which an individual believes that significant others, such as friends, coworkers, and family, think the individual should use a particular system. When applied to studies of extended TAM research, SI has consistently been shown to impact Perceived Usefulness (PU) by impacting users' beliefs about a technology's usefulness (Alalwan et al., 2016). When a system is sanctioned or advocated within an individual's network, the resulting social endorsement can validate their appraisal of the benefits of the system and thus increase the likelihood they will adopt the technology. SI can be particularly consequential in settings where peer approval, work culture, or community standards are particularly salient within the decision to use technology.

For example, Venkatesh and Davis (2000), in TAS2, observed that Social Influence (SI) is a significant predictor of Perceived Usefulness (PU) in organizational contexts where technology is being adopted through either a strong social endorsement by one's colleagues or team leader or because there is an expectation from management.

In these cases, users are more likely to believe that adopting a system will make them better at doing their job when it is being advocated for by people in their work environment that exert power (e.g., team leaders, managers and vice presidents) or people they respect among their peers. Zhou et al. (2010) found that social support from friends and family also produced an influential effect on mobile payment app users' evaluations of the advantages of using that technology in the context of fintech services. Support from others validates and reinforces the belief that technology is reliable and helpful.

One study in Chinese higher education looked at students' willingness to accept AI-based robots for educational purposes. It was found that, aside from job relevance and robot anxiety, most constructions in the model significantly influenced students' adoption intentions. This suggests that students' perceptions of the technology are influenced by social cues, such as peer endorsement, classroom interactions, and virtual networks. In addition, the students had a generally positive attitude toward the incorporation of AI-based robots into their education, acknowledging their expected impact on learning effectiveness and engagement. This suggests that the perception of a service being offered is positively and valuably reinforced by the prevailing social environment, comprising friends, classmates, and online communities, enhances acceptance (Algerafi, n.d.).

2.2.2 Awareness of Service

Service awareness (SA) is the degree to which users, particularly college students, are aware of a system or service and its related features and possible outcomes. SA is a relevant external variable in shaping Perceived Usefulness (PU), as modeled in

the Technology Acceptance Model (TAM). PU is the belief that using the technology will be beneficial in a school or personal context. Low SA may hinder students' use of the system, as students do not associate the features with necessary enhancements to their educational experience. Conversely, higher SA would allow students to better evaluate if the services met their needs, resulting in higher PU.

Research has consistently demonstrated this relationship. Lin & Lu (2000) investigated the relationship between knowledge of how to use an online service and perceived usefulness (PU). They found that when users became aware of the characteristics of the online service, PU increased because users could see that the proffered service was more efficient and convenient. Curtin et al. (2013) examined the awareness of academic support services by undergraduate university students in higher education, the researchers found that the more aware students were of the academic support services, the more they perceived them as useful and the more likely they were to access them. This study by Curtin et al. (2013) provided evidence that programs designed for the purpose of increasing awareness, such as orientations, faculty-led briefings, and targeted campus awareness campaigns, effectively improved PU among students. When students were aware of available resources, they were more likely to perceive them as useful and access them in their studies.

2.3 Theory of Perceived Ease of Use

Perceived ease of use (PEOU) refers to how easy people believe it would be to use a system. In AI finance, this reflects whether the investment platform is easy to use, designed intuitively, and requires limited learning. Systems that are deemed to be easy to use decrease the mental effort needed by the users and increases their overall

confidence regarding interacting with the system. Recent research on the adoption of fintech indicates that PEOU directly impacts user attitudes while also reinforcing perceived usefulness (PU). Systems that are easier to use are perceived to be more useful (Alshamaila & Alshurideh, 2023). For example, investors may have a favorable attitude of AI-driven robot-advisors when the system is easy to use (interface) and it is simple and transparent to understand (recommendation; Vilakshan, XIMB Journal of Management, 2024). Thus, it is anticipated that PEOU will have a favorable impact on users' attitudes toward AI-based investment tools.

2.3.1 Smartphone Self-Efficacy

Smart phone self-efficacy (SE) is how sure a person is that they can use a smartphone to do certain tasks well. In the Technology Acceptance Model(TAM), SE is an important outside factor that has a direct effect on Perceived Ease Of Use(PEOU), which is how easy a user thinks that it will be to use a system. People with high SE are better able to use application interfaces, fix small problems, and explore system features without getting frustrated. This skill makes things seem less complicated, which improves PEOU.

Compeau and Higgins (1995) showed that self-efficacy is a big factor in how people use technology because it makes them more confident that they can handle any technical problems that come up. In mobile-based services like mobile banking, e-learning, and mobile health, users with higher SE often need less help and feel less anxious when learning new features. This makes them think that the services are easier to use. In the mobile healthcare field, smartphone literacy was a strong predictor of PEOU in health app adoption. Hsiao and Tang (2015) found that mobile self-efficacy not only made PEOU better, but it also changed how people felt about using mobile learning systems in a roundabout way.

SE is especially crucial for college students. More proficient smartphone users can quickly become accustomed to new academic applications like campus service apps, mobile library systems, and e-learning portals. SE development is a worthwhile goal for both technology companies and educational institutions because of the potential for increased PEOU to hasten adoption and promote consistent use.

2.3.2 Quality of Internet Connection and Website

The two most important components of how effective a system feels to use are - the quality of the internet connection, and website design (Perceived Ease of Use (PEOU)). Even a platform that has an abundance of exciting features will soon feel difficult and frustrating to the user if they experience slow loading times, frequent disconnections, or unhelpful page designs.

A reliable and fast internet connection is the first step to a smooth user experience online. Without it, even the best designed websites quickly feel clunky and unresponsive. Quality of the website is considered too; an effortless feeling can be partially influenced by coherent layouts or usable features, as well as quick and clear navigation menus. Such ease of use is highly influential for consumer's decisions to continue using certain digital services, such as e-learning platforms, investment platforms and mobile banking.

According to Cyr et al. (2006), user impressions of ease of use are greatly enhanced by websites with attractive designs, simple navigation, and fast loading times. According to Tan and Teo (2000), user satisfaction and adoption rates are positively correlated with dependable internet connections and easily accessible systems. In

summary, people are more likely to persist with a system that seems easy to use and has higher technical performance and design quality.

2.4 Attitude Toward Using AI-Based Investment Tools

An attitude is defined as an individual's overall assessment—either favorable of unfavorable—of using a technology, and is an important factor in the Technology Acceptance Model (TAM). An attitude can be considered favorable when the user believes that the system is beneficial and effective when forming their behavioral intention and ultimately using the system. Regarding AI tools in investment, both trust and confidence are important variables influencing attitudes. Trust reflects the willingness to depend on AI tools with the understanding that the technology will operate dependably and securely, and in the best interests of users to the best of its capabilities; while confidence demonstrates a feeling of assurance in the user's own ability to use the technology and accurately interpret its outputs.

There is evidence to support this connection of attitudes, with studies showing that increased trust in AI technology leads to a heightened perception of positive attitudes toward its adoption by decreasing ambiguity and increasing perceptions of usefulness (Choung, David, & Ross, 2022). A similar relationship exists with confidence in the individual's own competence and reliability of the technology; increased confidence enhances comfort and decreases resistance to the adoption and use of the technology, leading to a strengthened positive attitude. Trust and confidence together are significant contributors to the attitudes towards AI-driven financial technologies that will ultimately affect ongoing acceptance and use.

2.4.1 Trust

Trust and confidence are essential to establishing favorable perceptions among users of AI-related financial technology. In this context, Trust is defined as a willingness or ability to depend on a System because of belief in its reliable operation, secure procedures, and meeting the end-user's objectives, especially under uncertain circumstances (McKnight et al., 2002). By contrast, Confidence encompasses the belief that the companies and creators of AI-driven Investment Tools will act responsibly while providing the end-user with accurate, transparent, and accountable results. Financially speaking, trust and confidence are critical to a user's decision-making process because these investments come with a great deal of uncertainty as well as an awareness of both a user's overall vulnerability as well as the potential for financial loss. Previous research has demonstrated that increased levels of trust increase confidence, thereby decreasing perceived uncertainty and creating a more favourable opinion of adopting AI-powered financial systems. (Gefen et al., 2003).

2.4.2 Confidence

Confidence extends beyond trust to include a sense of security that the AI system is robust, governed closely, and fulfilling users' expectations. A recent study found that clear algorithms, unambiguous risk communication, and trustworthy institutions can increase user confidence in AI technologies, which then leads to favorable attitudes toward adoption (Gillespie et al., 2025). Research in both robo-advisory and fintech platforms has shown that when users trust the dependability of AI systems, as well as the integrity of the provider, they will be much more likely to develop favorable attitudes toward and to move toward actual usage (Vilakshan, XIMB Journal of Management, 2024). Users must also be confident that the platform will not misuse their data or will not experience malfunction once deployed in situations involving a high risk of loss of funds, such as online banking or investing. As

articulated by McKnight et al. (2002), trust helps users feel more secure in using the platform, thereby reducing their degree of uncertainty. Confidence is a facilitator; if users have confidence in their own abilities to utilize the system, they will approach the system with a more positive mindset.

As stated by Gefen et al. (2003), trust does not only build loyalty, it also increases the propensity to use the system. This suggests that fintech platforms can influence trustworthiness, dependability, security, and a more personable customer service (efforts communicating reassurance) paired with training or tutorials, to encourage users to user the platform.

2.4.3 Theory of Perceived Risk

Although usefulness and ease of use promote adoption, perceived risk serves as a deterrent. Perceived risk is a user's assessment of possible negative consequences, such as loss of money, unauthorized access to sensitive data, abusive usage of risk information, or even technology deficiencies. In a sensitive space, such as financial decision-making, these factors often have a substantial influence on adoption. Recent research has identified potential negative impacts of high levels of perceived risk on attitudes toward fintech innovations, including applications of artificial intelligence (Padma Kiran & Sailaja, 2025). For example, investors concerned with algorithm faults or hacked computers may be more reluctant to accept recommendations from algorithms. Likewise, Heliyon (2025) found that perceived risk typically surpassed perceived benefit when trust was low, as a result, willingness to use technology was impaired. Therefore, it follows perceived risk likely influences attitude toward using AI-based investment tools negatively. Perceived risk is a user's worry when using a digital service. The concerns may relate to money (e.g. losing money), privacy (e.g. revealing personal information), or security (e.g. hacked accounts). A high perceived risk might deter a person from adopting a platform even if it is useful and easy to use.

For instance, consumers generally encounter sensitive financial information in fin-tech and investing platforms. For consumers, their perception of using these platforms might shift or change if they feel there is potential for fraud, issues with transactions, or misuse of their information. Featherman and Pavlou (2003) note that risky perceptions remain as one of the primary barriers to the use of e-services, including in systems of finance. For college students, risky perceptions have an effect not only on using technology but also when technology is at play. For example, students who use an e-learning platform to submit assignments or an online payment system to submit tuition payments may think about the security of their data—"What if my information is leaked?" "What if the platform shuts down right before the deadline?"—or system reliability. Even with apparent benefits in systems like convenience and time savings, students' perceptions of risk may yield resistance or reluctance to use the technology.

Perceived risks in the university context can be reduced to encourage more use of systems of university learning management systems, digital libraries, and online registration, but to also support long-term trust between students and the institution. Stated another way, reducing perception of risk goes beyond making technology better, it means creating an improvement in a student's trust in digital environments relating to the university.

2.5 Behavioral Intention to use AI-Based Investment Tools

Behavioural intention (BI) describes the user's expressed willingness to use and continue using a system in the future. According to the Technology Acceptance Model (TAM) , BI is the greatest predictor of an individual's actual use of a system. As stated previously, BI illustrates how individuals convert their attitudes into behaviors (Ajzen, 1991). About AI investment tools, BI also indicates the extent to which investors are prepared to depend upon algorithmic recommendations and robo-advisers for making financial decisions. Research in Fintech and Digital Banking has shown that investors who exhibit positive sentiments towards new financial technology (El-Massah et al., 2023) are more likely to have higher levels of BI. Because users perceive AI tools to be beneficial, user-friendly & dependable such as for portfolio planning or trading, these perceptions increase the probability of using the tools for these types of activities. Alternatively, if users perceive a certain level of risk associated with AI tools or have decreased confidence, this will reduce their likelihood of having such intentions. Research also shows that BI connects attitudes with actual usage and is influenced by other factors. These include social pressure, perceived control, and situational elements such as trust in rules and regulations (Padma Kiran & Sailaja, 2025). In studies related to technology use, recent findings show that user perceptions strongly influence behavioral intention. Chung et al. (2022) found that perceived usefulness and perceived ease of use shape users' attitudes and increase their intention to use AI-based financial systems. Yin et al. (2023) reported that trust, perceived risk, and social influence have a direct and significant effect on young investors' behavioral intention to use robo-advisors.

2.6 Research Framework

The Model of Technology Acceptance (TAM) referred to in section(s) 2.1 through 2.8 demonstrates how complicated it is to use technology because many elements contribute to how a person approaches using and using different technologies, including their own understanding of technology and outside influences on their

decision-making process when it comes to using them. Generally speaking, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the key elements of this model; however, other variables have been added to the model beyond PU and PEOU because they help to provide more comprehensive insight regarding students' intention to adopt and use technologies.

Social Influence (SI) and Awareness of Service (AW) demonstrate that adoption decisions are shaped not only by internal assessments but also by the environment. SI denotes the influence peers, family and the social system have on students' evaluations of usefulness, establishing that peer endorsement positively influences perceptions of the value of technology. AW enhances PU by ensuring students are aware of the technology's existence, features, and benefits (including functionality). Awareness increases students' ability to appreciate technology's relevance to their educational and personal needs, improving belief in PU.

Smartphone Self-Efficacy (SE) and Quality of Internet Connectivity and Site Quality (QI) bring attention to the involvement of both individual competence and adequate technology at the organization in that to determine PEOU. SE is the student's belief in their ability to locate, troubleshoot, and use mobile applications (for investment purposes) correctly. Students with high SE consider applying a new platform less unpleasant and easier to learn. QI ensures that you interact with a system in a manner that is seamless, efficient, and beneficial. With a stable internet connection and structurally sound websites or applications, end-users are less likely to become frustrated when learning, and they will find that the system is easy to use.

In addition to functional factors, the model incorporates psychological and trust factors that impact user attitudes. Perceived Risk (PR) serves as a roadblock to influence the unknown aspects, such as privacy issues, monetary loss, or technology

failure. When students perceive a greater risk attached to using AI-related investment tools it will lead them to have a lower positive view of these tools. By contrast, when students develop a trust and confidence in these tools, it will increase their positive view of them. Trust is based on the belief that the platform is safe, open, and dependable. Confidence is more personal and represents a student's belief that they can successfully engage with the tool. Therefore, together, trust and confidence work to reduce students' ambivalence about engaging with AI systems, allowing them to form a more positive attitude toward these systems based on their functioning and psychological safety. Another aspect of the framework presented in this study is Subjective Norm (SN). This construct captures social influences on Behavioral Intention (BI). SN illustrates that using AI-related investment tools is not only an individual decision; it is also affected by what friends, co-workers, and other significant groups think and how they approve. BI goes on to describe students' actual readiness to engage in action. BI combines attitudinal and social constructs with perceptions of risk, trust, and confidence to determine whether students will continue using AI-related investment tools going forward.

In conclusion, this integrated model demonstrates that students' acceptance of AI technologies is not determined by a single factor but by the interplay of technical performance, social validation, individual competence, and emotional assurance. By combining constructs from TAM, Extended TAM, and TRA, the framework offers a holistic perspective where adoption decisions are shaped by usefulness, ease of use, awareness, infrastructure quality, self-efficacy, trust, confidence, perceived risks, and subjective norms. Understanding these dynamics is essential for promoting long-term adoption of AI-based investment tools among students and ensuring that both functional and psychological needs are addressed in the design and implementation of such technologies.

2.7 Research Gaps

Though prior research has experimented with Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA) in ascertaining technology uptake in general contexts such as e-learning platforms, mobile banking, or e-services, the majority of research addressing these models in academic journals have established TAM and TRA within the student context with broader technology categories, and very little research has explored AI-based investment technology in Malaysia, specifically targeting students. At the same time, constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) have been well documented in research with substantial evidence of explanatory power, the significance of external and psychological factors such as Trust, Confidence, Social Influence, Awareness, Smartphone Self-Efficacy, and Quality of Internet Connection - factors which are relevant to the next generation of young investors who predominantly operate through technology.

In addition to a focus on financial professionals and general investors, the concept of university students understands how they perceive risks, develop Trust, and intention to engage in using AI technology will be missing in the literature, given that university students will be the next generation of investors and heavily influenced by the academic peer environments (collegial) and technologies that invests to signal their affluence, this too requires attention to develop more understanding. These research gaps would present the opportunity to add to the literature on TAM and its scope to capture contributions by extending it beyond adoption of technology or instruments for fintech technologies.

2.8 Conclusion

This chapter examined the theoretical and empirical foundations associated with the study. It started off with the introduction of the guiding models of Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA) and then discussed the core constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Risk (PR), Trust, and Confidence. We then continued to present external and contextual variables such as Social Influence (SI), Awareness of Service (AW), Smartphone Self-Efficacy (SE), and Quality of Internet Connection and Website (QI). Lastly, we assessed the psychological and social dimensions of Attitude, Subjective Norm, and Behavioral Intention to round out our understanding of technology adoption behavior.

Ultimately, the discussion established that college students' acceptance of AI-based investment tools is influenced by a complex constellation of functional benefits, social proof, psychological ease, and infrastructure support. It is also imperative to note that gaps in previous research highlight the need for researchers to consider various constructs as part of an expanded TAM for college students' adoption behavior in an fintech context. With that said, these discussions have laid the foundations for the study's conceptual framework and hypotheses, which will be discussed in the chapter on research methodology.

Chapter 3: Research Methodology

3.0 Introduction

The methods of research for this study are described in this chapter. In this chapter, the researcher identified the design of the research, how the data were collected, how the sample was selected, the instruments used for the research, the constructs measured in the research, and how the data were analyzed. The chapter will demonstrate how the study was designed and conducted in an effective and orderly manner to achieve valid and reliable results.

3.1 Research Design

The research conducted employed a quantitative methodology utilizing a cross-sectional survey as its primary means of data collection. Quantitative methodology concentrates on gathering and processing numerical data, with the goal of discerning patterns; computing averages; determining relationships; and reaching general conclusions. Quantitative research is typically used in the natural sciences, social science and in behavioral studies. Quantitative research typically employs statistical techniques such as descriptive statistics or regression analyses, to analyze numerical data.

The theoretical framework of the study has incorporated the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), as well as an expanded TAM framework. In the TAM, the perception that an application's ability to be useful is to be directly correlated to both the user's attitude toward the application and the user's intent to use the application. Similarly, in the TRA, the user's attitude toward an

application, as well as the user's subjective perception that he/she is being influenced by others to use an application, are believed to be correlated to the user's behavioral intent to utilize an application, as well as actual utilization of an application.

The expanded TAM framework encompasses variables that are used together to influence behavioral intentions (BI's) and actual usage (AU's) of AI-powered investment tools. These additional variables comprise awareness of AI Services (AW), Self-Efficacy (SE) for using a smartphone, quality of internet and website (QI), and the User's level of Confidence, Attitude, and Subjective Norm (SN) regarding the investment strategy. All these variables are correlated with the user's perceived usefulness (PU), perceived ease of use (PEOU), Trust in AI, perceived risk associated with using AI, and Social Influence (SI). Demographic variables, such as Age and Gender, serve as moderating variables in this study.

3.2 Research Methodology

The methodology extended to the Technology Acceptance Model (TAM) which includes factors like Technical Factors - that is perceived usefulness, perceived ease of use and quality of internet and website (QI); Psychological Factors - these are trust in AI, perceived risk, confidence and self-efficacy. Technical Factors will give an evaluation of how easy, useful and trustworthy the AI based investment tools are. The Psychological Factors reflect students' individual perceptions, concerns and confidence regarding their usage of AI tools. Social Factors consist of Social Influence and Subjective Norm which represent the impact from people's expectations around them. Awareness of Service shows whether there have been prior experiences/familiarity with AI based investment tools. The overall Attitude reflects a student's opinion of AI based investment tools and Behavioral Intention is used to predict a student's actual usage of the tools in alignment with TAM and TRA principles for decision-making.

3.3 Development Of Research Framework and Hypothesis

As described in Sections 2.1–2.8, the expanded Technology Acceptance Model (TAM) indicates that the technology adoption dynamic entails multiple interrelated factors, involved both externally and internally. While the basic concepts of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are still relevant in understanding user acceptance, examining further determinants introduces greater richness and allows for a deeper understanding of student technology adoption behavior. Based on previous research in AI and FinTech (Chung, 2022; Yin, 2023), the selection of Behavioral Intention (BI) as the main outcome variable is justifiable as both PU and PEOU were shown to impact attitude toward AI based financial tools which strongly predicted BI. Trust, perceived risk, and social influence were confirmed by Yin et al. (2022) as significantly increasing the likelihood of young investors adopting Robo-Advisors. These findings warrant the use of TAM-TRA constructs to predict BI for University Students within the field of AI-Based Investing.

Social Influence (SI) and Awareness of Service (AW) underscore how decisions about adopting technology are informed by more than an individual's evaluation of the technology, and how those factors stem from the student's social surroundings. SI captures the influence of a peer group, family members, and larger social networks, in shaping the student's view of usefulness for technology, identifying technology as useful in many instances because of the further endorsement of it among others. AW supports PU in that it ensures a student is adequately informed of the existence and the functional features and benefits of the AI-based investment tools. With awareness of the technology present in their knowledge, and with sufficient

content and user involvement, students will recognize the technology as relevant to their academic or personal goals and thus increase PU.

Smartphone Self-Efficacy (SE) and Quality of Internet Connection and Website (QI) underscore the importance of both individual capability and technological infrastructure in influencing PEOU. Student smartphone self-efficacy (SE) indicates a student's level of confidence in their usage of mobile applications for investment purposes, including the ability to navigate the application system, troubleshoot basic issues, and utilize different features efficiently. Students with a higher SE believe that they will have fewer problems managing these new applications and will find these new systems easier to use. A student's quality of internet and website (QI) refers to the extent to which the system operates seamlessly and efficiently. When a student has stable, reliable internet service and is using a well-designed website or mobile application, this lessens frustration and makes the application easier to navigate. These elements help influence a student's perception that these types of tools will be easy to use.

Besides functional factors, the framework includes psychological and trust-related factors that influence a student's attitude. Perceived risk (PR) addresses a student's concerns about things like their data being kept private, potential for financial loss, and uncertainty regarding system errors. Due to all the associated concerns, a student's overall attitude towards using AI-based investment tools would be markedly reduced with an increase in perceived risk (PR). Conversely, trust and confidence would improve a student's attitude. Trust refers to a student's perception that a platform is secure, transparent, and reliable. Confidence reflects the belief that a student has in his/her ability to use the application effectively. When put together, these factors are the yin and yang of a student's doubt and reassurance. Ultimately, positive attitudes rely on both the performance of the platform and psychological comfort.

The framework includes the Subjective Norm (SN) which ties an individual's social circle to their Behavioral Intention (BI). When determining BI, students are influenced by what others think of their decision to use AI technology, as well as how other important social groups view them (e.g., family). The BI is indicative of how likely a student will be to actually engage with an AI tool and reflects the combination of the students' attitude toward using that type of technology, the SN of students' friends and peers, and their perceived risks of, trust in, and comfort with using these tools. The BI can also be utilized to estimate students' Actual Usage of AI tools in the future.

This study shows that acceptance of AI technology by students is shaped by personal use, the relationship they have with the organisation or institution providing the application, and their ability to use the tool. The combination of these factors like technical performance, social validation, individual competency, emotional security leads to a better understanding of why a student chooses to adopt or not adopt a particular application as well as how an institution can develop AI-based investment tools that will meet both functional and psychological needs. Therefore, understanding how these dynamics work together can help with the long-term adoption of AI-based investment tools by students. Additionally, the use of the constructs from the Technology Acceptance Model (TAM), Extended Technology Acceptance Model (Extended TAM) and Theory of Reasoned Action (TRA) provides a complete model for determining how students will decide to adopt AI technology.

Hypotheses of the study

H1: Perceived Usefulness affects Attitude Toward AI in Investing.

H2: Perceived Ease of Use affects Perceived Usefulness.

H3: Perceived Ease of Use affects Attitude Toward AI in Investing.

H4: Trust in AI affects Attitude Toward AI in Investing.

H5: Perceived Risk affects Attitude Toward AI in Investing.

H6: Social Influence affects Attitude Toward AI in Investing.

H7: Attitude Toward AI in Investing influences Behavioral Intention Toward the Use of AI Investment Tools.

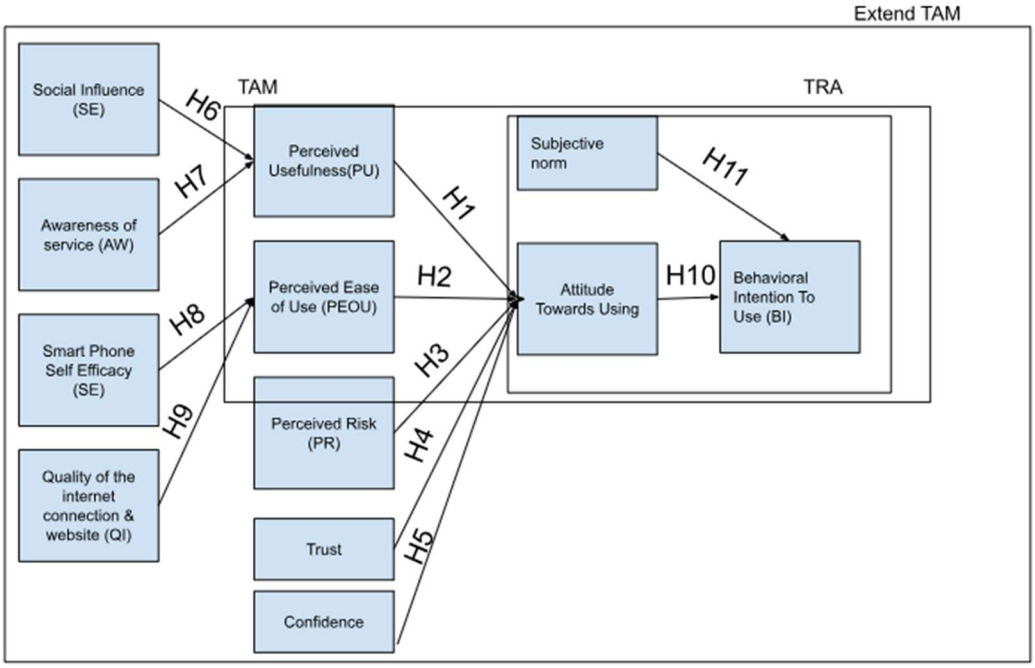
H8: Awareness of Service affects Perceived Usefulness.

H9: Smartphone Self-Efficacy affects Perceived Ease of Use.

H10: Quality of Internet Connection and Website affects Perceived Ease of Use.

H11: Confidence affects Attitude Toward AI in Investing.

Figure 3.1: Conceptual Framework



3.4 The Sample

The study focuses on undergraduate students from Universiti Tunku Abdul Rahman (UTAR). Students from UTAR were chosen as the sample of interest due to their being a digitally literate group, and they will potentially be future investors with increasing exposure to financial technology based on AI. All students in university are considered young adults, therefore they have a tendency to use mobile apps, use online investment sites, and take advantage of new financial technology and thus the most appropriate source to study the intention of the user to use artificial intelligence as an investment tool. Participants in this research will be from the different faculties of UTAR and will cover a variety of academic levels. This will provide a comprehensive view of how students use technology, invest, and view artificial intelligence as part of making financial decisions.

3.4.1 Sampling Technique

For this investigation on technology adoption and usage, the researcher used a convenience sampling strategy which provides a quicker way of acquiring and accessing participants for research whilst using less resource expenditure than other sampling methodologies. The target sample consisted of undergraduate students enrolled in UTAR; the students listed above will be more accessible through online platforms, classroom distribution, and peer networks; therefore, convenience sampling was a viable method for this study's design. Convenience sampling is frequently utilized in the fields of technology adoption and behaviour analysis, where researchers aim to investigate correlations between constructs rather than making inferences about a larger population (Eitkan et al., 2016).

Convenience sampling is used to gather information from a group of individuals who are most readily available to the researcher. Most of the studies conducted using

convenience sampling are exploratory and explanatory in nature, where the need for access and relevance are more important than statistical representativeness. Previous studies on technology acceptance have used convenience sampling to investigate college students since they are a group of people who understand digital technology and can evaluate new technologies (Hair et al., 2017). Therefore, the use of convenience sampling will meet the objectives of the present study.

3.4.2 Sample size and Power Analysis

In this research, several methodological assumptions were made in order to support the statistical framework used to analyse the data. First, to justify the sample size assumption, the study still followed the general recommendation that the minimum number of respondents should be sufficient to detect medium effects with adequate statistical power. Consistent with Kock and Hadaya (2018, p. 342), the target of 150 to 200 respondents remains appropriate, as this sample size is greater than the minimum required to provide stable estimates. In addition, the study assumed a medium effect size ($f^2 = 0.15$), alpha level = 0.05, and power between 80% and 95%, which is consistent with standard power analysis guidelines. Using G*Power with six predictors for the most complex model, the required minimum sample size was 165. These assumptions suggest that the achieved sample size meets recommended considerations for detecting significant relationships and reduces the risk of Type II error.

For the measurement model, the assumption for reliability was that Cronbach's Alpha values should be above the 0.70 cut-off value (Hair et al., 2017), which indicates internal consistency among the indicators. Since SPSS was used for analysis, reliability was examined through Cronbach's Alpha rather than composite reliability. Validity was assessed through factor analysis, where the assumptions were that the Kaiser-Meyer-Olkin (KMO) value should exceed 0.60 and Bartlett's Test of Sphericity should be significant. Additionally, factor loadings were expected to exceed 0.50 to indicate

that the items adequately represent their respective constructs. These assumptions suggest that the constructs are unique and that the indicators are measuring what they are supposed to measure, which contributes to the meaningful interpretation of the structural relationships.

For the structural model, the study assumed that relationships between constructs are linear and that multiple regression is appropriate for the variables under investigation. It was further assumed that the classical regression assumptions normality, linearity, homoscedasticity, and absence of multicollinearity were met for valid significance testing. These assumptions imply that regression coefficients, R^2 values, and moderation analyses can be interpreted with confidence. In particular, the moderation effects of demographic variables such as age and gender will only be meaningful if a sufficient sample size is retained across sub-groups, which is supported by the targeted sample size in this study. The minimum sample size needed for this research using the G*Power analysis is 165 participants to obtain a medium effect size ($f^2 = 0.15$), have a significance level of .05, and obtain an acceptable level of power (.80) with six predictors in the most complex regression model. Thus, it can be determined that a target sample size of 150 to 200 will provide sufficient power to reliably estimate parameters with a low likelihood of making a Type II error.

3.5 Data Collection Methods

To gather primary data, an online survey was created using Google Forms. It took about 10–15 minutes for participants to finish and contained three sections. The first section contained demographic details, such as: gender, age, college, educational background, and experience with investing. The second section asked potential respondents whether they had ever used or were aware of any AI-based investing platforms, for example Moomoo, Wahed Invest, Bloomberg, and Eikon. The third

section had measures with multiple statements on a five-point Likert scale where "1" meant "Strongly Disagree" and "5" meant "Strongly Agree."

To ensure ethical standards, participants were informed about the purpose of the research, assured that participation was voluntary, and notified that all responses would remain anonymous. No personally identifiable information was collected.

3.6 Operations Definition of Research Model Constructs

Social science constructs can be interpreted in several ways, which can lead to confusion if definitions are not clear. Therefore, this study will use operational definitions for each construct, which is the concept that is defined as and measured individual measurement items within that construct. The operational definitions used in this current study are derived from reliable validated scales from previous research, but items have been slightly modified for the population of university students using investment tools based on AI. This will both retain reliability and context.

a) Perceived Usefulness (PU)

Perceived Usefulness is the degree that students feel that AI-based investment applications, will help them improve their investment performance, make better financial decisions, or save time and effort. For example, robo-advisers and predictive analytics systems, are created to offer quick and accurate recommendations to consumers for better allocation of their portfolios. When students feel that these systems are useful, they are more likely to use them. PU was first identified as an important determinant in Technology Acceptance Model (TAM), by Davis (1989), and most recently, PU has been shown to significantly affect the user's adoption of AI in several fintech studies.

b) Perceived Ease of Use (PEOU)

PEOU relates to the extent to which students feel that the act of using AI-based investment platforms is easy, simple, and requires little effort on their part. When the system interface is simple to use and recommendations are simple to understand, users become less frustrated and have much more confidence to use the system. According to the research, PEOU not only has a direct impact on adoption but also increases Perceived Usefulness because if the technology is easier to use, the user is more likely to see it as being useful (Davis, 1989). With university students, systems that have simple navigation and are simple to access are especially important when considering positive attitudes toward adoption.

c) Perceived Risk (PR)

Perceived Risk is the apprehension that students have about potentially adverse consequences that could happen in using AI to make financial decisions. Students are primarily concerned with losing money because of an error made by the system and/or due to potential security breaches or misuse of their personal information. Since students are very sensitive to their financial investments, many students will not use AI-powered investment tools if they have even the slightest doubt regarding the system's reliability. Featherman and Pavlou (2003) identified Perceived Risk as a significant barrier to using online financial services. For many students, the anticipated advantages of using AI-powered investment tools are outweighed by the possibility of system failure, data breaches, or ultimately fraud. Because of this, many students will hesitate to consider AI-powered investment tools. Therefore, PR is likely to negatively influence attitudes towards investment tools with AI.

d) Trust (TRU)

Students' trust in AI-based systems stems from their belief that those systems are safe, dependable, and transparent. In financial contexts, people will tend to establish a level of trust with users when there is uncertainty on the part of users regarding how the system's internal workings. The trust factor is a direct factor to user attitude and stronger behavioral intention as identified by Gefen, et al. 2003. For students, trust is built around three basic beliefs. They believe the system will keep their personal information secure, will make good decisions based on good data, and will use only sources with a good reputation for data quality.

e) Confidence (CON)

In contrast to trust, which represents students' reliance on AI tools, confidence embodies a sense of assurance students feel that AI tools are adequate, trustworthy, well-regulated, and able to support complex financial decision-making. While trust deals with student's reliance on these systems, confidence relates to a sense of personal security when engaging with the system. According to McKnight et al. (2002), confidence in system integrity increases the user's feeling of ease with reduced uncertainty and improved attitudes towards usage. For students, confidence could be built through limited ambiguity in systems communication, visible protective mechanisms, and support systems that mitigate the student's uneasiness surrounding the tools stability.

f) Social Influence (SI)

Social Influence is defined as the degree to which students' decisions to adopt AI-driven investment applications are shaped by the views or behaviors of peers, family, or educators. The academic based context is often a scenario where students are vulnerable to group norms that tend to offer social validation when friends or authority

figures support the technology. Venkatesh and Davis (2000) noted that social influence often improved perceptions of usefulness and adopting the technology. For instance, if classmates or lecturing staff tout the benefits of using AI applications to learn about financial investments, students may see the AI-driven platforms as useful and necessary.

g) Awareness of Service (AW)

Service Awareness is indicated as the degree of students' understanding about the existence, features, and benefits of AI-based investment platforms. Awareness is important to behavioural PU, students who are more aware of the features/functionality (K), can better assess the value. Lin and Lu (2000) showed that awareness had a significant impact on efficiency and convenience. For example, students might be made more aware of AI tools through campus advertising, workshops, or peer conversations about AI tools, increasing students' willingness to use them.

h) Smartphone Self-Efficacy (SE)

Smartphone self-efficacy is the degree to which the student believes they can competently use a smartphone to access an AI-based investment platform and use the features/operated correctly. Students who believe they have high SE feel confident discovering the platform features, fixing technical problems, or adapting to new systems. Compeau and Higgins (1995) showed that SE is a strong indicator of PEOU and decrease user anxiety. The other students' smartphone SE will be much of the ease of use of mobile-based financial apps. Smartphone SE will lessen the apprehension of the students while adopting mobile-based finance apps and enhanced PEOU, which in turn leads to the adoption of mobile-based finance app.

i) Quality of Internet and Website (QI)

The quality of the Internet and Website refers to how stable the Internet connection is and what the interface of the platform looks like and how usable it is. A system may have good features, but if the Internet connection is poor or the layout is confusing, users can become discouraged from using the platform. Cyr et al. (2006) found that easy navigation or layout, aesthetics, and reasonable load times facilitate improved perceived ease of use. User accessibility, reliable Internet access, and user-friendly user interface (UI) design are important aspects of usability for students using AI platforms, or students will become frustrated and find it increasingly difficult to use the technology consistently.

j) Attitude (ATT)

Attitude captures students' general assessment (positive or negative) of using AI-based investment tools. Positive attitudes derive from students' perception of the systems as useful, helpful, and reliable. Ajzen (1991) noted that predictive models of intention need to account for attitude, as people generally adopt behaviour that is evaluated positively. In this instance, trust and confidence are significant contributors to students' attitudes, leading students to be more comfortable relying on recommendations produced by AI programs.

k) Subjective Norm (SN)

Subjective Norm pertains to how socially pressured students believe they should be to use AI-based investment tools. The pressure can be from friends, classmates, a professor, a parent, or a family member. Fishbein and Ajzen (2005) established subjective norms as one of the key variables in behavioural intention indicating peoples intentions to engage in a behaviour in order to act in accordance with the group's expectations. In the context of students, if most peers use the Ai

platform for their coursework or for investing, then other students will likely use the platform to avoid being left behind.

l) Behavioural Intention (BI)

Behavioural Intention refers to students' readiness and probability to practice the use of AI-based investment tools soon. BI is the strongest predictor of actual system use and connects attitudes, subjective norms, and self-efficacy beliefs with behavioural engagement (Ajzen, 1991). In this study, BI represents the extent to which students are predisposed to using AI-based investment tools in the context of investing, based on their evaluations of usefulness, ease of use, trust, and social influence.

Table 3.1: Outline of Measurement Range for Every Variable in Current Research

Construct	Measurement Item (5 Likert scale:1= Strongly Disagree, 5= Strongly Agree)	Source
Perceived Usefulness (PU) (Adapted)	PU1. Using AI-based investment tools improves my investment performance. PU2. AI-based tools make it easier to make investment decisions. PU3. AI-based tools enhance my productivity in managing investments. PU4. AI-based tools are useful in my investment activities.	Davis (1989); Venkatesh & Davis (2000); Abbad (2023)
Perceived Ease Of Use (PEOU) (Adapted)	PEOU1. Learning to operate AI-based investment tools is easy for me. PEOU2. It is easy for me to become skillful at using AI-based investment tools. PEOU3. I find AI-based investment tools easy to use. PEOU4. Interacting with AI-based investment tools does not require much mental effort.	Davis (1989); Venkatesh & Davis (2000); Abbad (2023)
Social Influence (SI) (Adapted)	SI1. People who influence my behavior think I should use AI-based investment tools. SI2. People whose opinions I value prefer that I use AI-based investment tools. SI3. People important to me recommend the use of AI-based investment tools.	Venkatesh & Davis (2000); Venkatesh et al. (2003); Algerafi (n.d.)
Awareness Of Service (AW) (Adapted)	AW1. I am aware that AI-based investment tools are available for use. AW2. I know about the features of AI-based investment tools. AW3. I am aware of the benefits of using AI-based investment tools.	Lin & Lu (2000); Curtin et al. (2013)

	AW4. I know where to access AI-based investment tools.	
Smartphone Self Efficacy (SE) (Adapted)	SE1. I am confident in my ability to download and install AI-based investment apps on my smartphone. SE2. I can troubleshoot common smartphone issues when using investment tools. SE3. I can learn how to use new investment apps without help. SE4. I can use smartphone features to optimize my investment activities.	Compeau & Higgins (1995); Hsiao & Tang (2015)
Quality of Internet Connection & Website (QI) (Adapted)	QI1. The internet connection I use for AI-based investment tools is stable. QI2. The website/app for AI-based investment tools loads quickly. QI3. The layout of the website/app is clear and easy to navigate. QI4. The website/app provides smooth interaction without errors.	Cyr et al. (2006); Tan & Teo (2000)
Perceived Risk (PR) (Adapted)	PR1. Using AI-based investment tools could cause me to lose money. PR2. I am concerned about the security of my personal data when using AI-based investment tools. PR3. I am worried that my information could be misused by AI-based investment tools. PR4. Using AI-based investment tools involves too much uncertainty.	Featherman & Pavlou (2003); Alalwan et al. (2016)
Trust (Adapted)	T1. I trust AI-based investment tools to perform reliably. T2. I believe AI-based investment tools protect my best interests. T3. AI-based investment tools are trustworthy. T4. AI-based investment tools provide accurate information.	McKnight et al. (2002); Gefen et al. (2003); Alalwan et al. (2016)
Confidence (Adapted)	C1. I am confident that I can successfully use AI-based investment tools.	McKnight et al. (2002); Algerafi (n.d.)

	C2. I feel certain that I can make sound decisions using AI-based investment tools. C3. I can rely on my own judgment when using AI-based investment tools.	
Attitude Towards Using (ATU) (Adapted)	ATU1. Using AI-based investment tools is a good idea. ATU2. I have a positive attitude towards AI-based investment tools. ATU3. Using AI-based investment tools is beneficial. ATU4. I like the idea of using AI-based investment tools.	Davis(1989); Venkatesh et al. (2003); Abbad (2023)
Subjective Norm (SN) (Adapted)	SN1. People important to me would approve of my using AI-based investment tools. SN2. People whose opinions I value support my use of AI-based investment tools. SN3. My peers think I should use AI-based investment tools.	Davis (1989); Venkatesh et al. (2003); Abbad (2023)
Behavioral Intention To Use (BI) (Adapted)	BI1. I intend to use AI-based investment tools in the future. BI2. I will regularly use AI-based investment tools. BI3. I will recommend AI-based investment tools to others. BI4. I plan to explore more features of AI-based investment tools.	Ajzen & Fishbein (1980); Venkatesh et al. (2003)

3.7 Questionnaire Design

The questionnaire was developed to collect data on respondents' demographics, awareness of AI-based investment tools, and perceptions of constructs from the extended TAM–TRA framework. Section A included demographic information such as age, gender, faculty, and investment experience. Section B measured respondents' awareness and prior use of AI-powered platforms such as robot-advisors and trading applications. Section C focused on construct measurements including perceived usefulness, perceived ease of use, trust in AI, perceived risk, social influence, subjective norm, confidence, self-efficacy, awareness of service, quality of internet and website, attitude, behavioural intention, and actual use. All items were adapted from validated scales and adjusted to suit the Malaysian student context. A five-point Likert scale ranging from "strongly disagree" to "strongly agree" was used to capture perceptions. The questionnaire was piloted with a small group of students to refine wording before being distributed online through Google Forms, ensuring clarity, accessibility, and anonymity for participants.

3.8 Data Processing

All completed questionnaires were first screened for completeness and consistency. Responses with substantial missing data or obvious response patterns such as straight-lining were removed. The valid responses were then coded and entered Microsoft Excel and subsequently imported into IBM SPSS Statistics for analysis. Prior to conducting the main analyses, data cleaning procedures were carried out, including checking for out-of-range values, reverse-coded items where applicable, and missing values. Descriptive diagnostics were inspected to ensure that the data were suitable for further analysis. Composite scores for each construct (Perceived Usefulness, Perceived Ease of Use, Social Influence, Awareness of Service, Smartphone Self-Efficacy,

Quality of Internet and Website, Perceived Risk, Trust, Confidence, Attitude, Subjective Norm and Behavioural Intention) were computed by averaging the relevant items as specified in Table 3.1.

3.9 Data Analysis

Path Analysis in this research used a sequential, stepwise procedure based on multiple regression to explore the suggested pathways where one construct influences another within the proposed Model. Each dependent variable was treated independently (separately) during the Path Analysis so that hypotheses regarding causal relationships could be evaluated by order of occurrence, referencing the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA), both of which state that earlier constructs should help predict later behavioural responses. The authors believe that Path Analysis represents a suitable alternative when SEM methods are not practical due to the nature of the data being analysed (Hair et al., 2019).

To perform statistical data analysis, IBM SPSS Statistics was used to analyse all data related to this research study according to the research objectives via descriptive statistics (frequencies, percentages, means and standard deviations) to describe the demographics of the study participants and the measures' central tendency,

The second phase of data analysis consisted of measuring Cronbachs alpha to determine the reliability of each measure based on their Cronbachs alpha. Items with a minimum reliability score of 0.70 which is essentially meaning that the respondents answer within an acceptable range were used for further analysis as those items correlated directly to their associated constructs.

The final phase of data analysis included examining the relationship between two variables, such as the dependent variables and the independent variables, using

multiple linear regression analysis. This approach allowed the study to assess the magnitude, direction, and statistical significance of the relationship between the constructs, which is shown in the research framework.

Ultimately, researchers performed multiple linear regression analyses on their proposed research hypotheses. Each of these analyses was performed separately; that is, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioural Intention were all the dependent variables in their respective regression model. Independent variables for each regression model were identified based upon the respective conceptual models of technology acceptance.

Researcher's decision-making process for accepting or rejecting each of the proposed hypotheses relied upon the following criteria that prior technology adoption researchers identified for conducting multiple linear regression analyses (Davis, 1989): 1. Statistical significance of regression coefficients (p-values), 2. Standardized Beta Values, and 3. Overall assessment of the quality of the regression model as determined by R2 and Adjusted R2.

Before conducting hypothesis tests, the assumptions of Multiple Linear Regression were confirmed to be met prior to establishing the validity of the results from the analysis. The normality of the residuals was determined using histograms and P-P graphs, which indicated that they followed an approximate normal distribution. The scatterplots of standardised residuals plotted against predicted values were examined for linearity and homoscedasticity, and they did not display evidence of any significant curvature or funnel effect; indicating that the equations did not exhibit either of these non-linearities. Variance Inflation Factor (VIF) and Tolerance values were used to examine Multicollinearity; all VIF and Tolerance values were within the acceptable range (VIF < 10; Tolerance >0.10); therefore, there was not a concern regarding serious Multicollinearity. The independence of the errors was assessed via the Durbin-Watson statistic with the numbers being close to 2.0 indicating that autocorrelation was absent. The preceding diagnostic values confirmed that the

regression assumptions were sufficiently satisfied and that the resultant estimated models were both reliable and valid for future use.

3.10 Summary of the Chapter

In summary, this chapter has presented the methodological approach of the study. It explained the research design, sampling strategy, and data collection methods, as well as the development of the research instrument and construct measurements. It also described the data processing and analytical techniques used. By integrating TAM, TRA, and extended constructs into a single framework, this methodology provides a holistic approach to understanding the behavioral intention and actual use of AI-based investment tools among UTAR students. The use of SmartPLS 4 ensures rigorous analysis of both measurement and structural models, thereby enhancing the validity and reliability of the findings and contributing meaningful insights to both theory and practice.

Chapter 4 Analysis And Research Findings

4.0 Introduction

The results of the research study for this chapter are based upon the results from (2) 210 respondents completing valid questionnaires collected from the students of Universiti Tunku Abdul Rahman (UTAR). The analysis has four major areas of study: (1) the analysis of descriptive statistics, including respondent demographic characteristics, and the central tendency measures of the constructs examined by the study; (2) the results of the evaluation of the reliability of the scales employed in this research; (3) the analyses of regression and correlation analyses used to evaluate the Hypotheses tested in this study; and (4) Chapter Four concludes with a summary of the findings and the transition to Chapter Five. The data for this study was collected through the employment of face-to-face recorded interviews using a structured survey that were conducted during the month of November 2025. The intended population for this study was composed of students enrolled at UTAR, with a focus on the foundation and undergraduate student level. The total number of cases for this study sample was 200. To select the student respondents for the present study, a convenience sampling method was used to select participants from within the study population. In total, 213 fully completed survey forms were received from all faculty and student respondents participating in the study.

4.1 Descriptive Analyses

4.1.1 Respondent Demographic Profile

Students and faculty at UTAR (Universiti Tunku Abdul Rahman) were the respondents for this research, with a total of 213 surveys completed through face-to-face distribution in November 2025. Quota sampling was used to ensure proper

representation in terms of gender, age group, faculty, education level and investment experience.

The sample consisted of a larger proportion of female respondents (59.2%) compared to male respondents (40.8%), showing that more female students participated in this study.

For age group, the categories for older respondents were combined into a single group called “24 and above” due to the very small number in those categories. The results indicate that 51.2% of respondents were aged 18–20, followed by 45.1% aged 21–23. Only 2.4% were aged 24 and above, which shows that the majority of respondents are younger university students.

In terms of academic background, most of the respondents were from the Faculty of Accountancy and Management (39.9%), followed by Foundation Studies (26.3%), while 9.9% were from the Faculty of Creative Industries. The remaining 23.9% came from other faculties. This shows that the responses are more concentrated among business-related academic fields.

The education level results show that 65.3% of respondents were undergraduate students, followed by 31.9% foundation students, while only 2.8% were Master’s students and Doctorate/PhD students. This distribution reflects UTAR’s overall student population where undergraduates form the majority.

Based on investment experience, 65.3% of respondents reported having no investment experience, while 21.1% had less than one year of experience. Only 13.6% of respondents had three years and above of experience. This finding is expected as most respondents are still studying and have limited exposure to real investment activities.

Overall, the demographic results indicate that the participants of this study were mainly female, younger-aged university students, mostly from business-related faculties and with limited investment experience which aligns with the characteristics of student investors who are still in the early stage of learning about financial decision-making.

Table 4.1: Demographic Profile

Demographic Variable	**%**	**n**
Gender		
Female	59.2	126
Male	40.8	87
Age group		
18-20	51.2	109
21-23	45.1	96
24 and above	2.4	5
Faculty		
Faculty of Accountancy & Mangement (FAM)	39.9	85
Foundation Studies	26.3	56
Faculty of Creative Industries (FCI)	9.9	21
Others faculty	23.9	51
Education Level		
Foundation Studies	31.9	68
Undergraduate	65.3	137
Master's Degree	1.9	4
Doctorate/ PhD	0.9	2
Investment Experience		
None	65.3	139
Less than 1 year	21.1	45
3 years and above	13.6	29

In Section B1, results regarding the familiarity of 22 Artificial Intelligence-based (AI) investment and research platforms were evaluated. The data produced a pattern showing a great deal of concentration of awareness of these platforms among respondents who took the survey. The platform "Moomoo Malaysia" ranked highest in familiarity, at 54.5% of respondents, due in part to their aggressive marketing strategy and continued exposure to young Malaysian investors; therefore, Moomoo is the name of the platform that is the most highly recognised AI-based Investment Tool with University Students. The next level of awareness was for the platform "AI StockMaster" at 37.1%; this demonstrates to a moderate degree recognition among University Students, but still far below that of Moomoo.

The awareness of all other tools after these two platforms showed a dramatic decline; for example, Eikon (Refinitiv, LSEG), Bloomberg Terminal, StockInsights.ai, FinChat.io, FinWorld, and FinRobot all had less than 10% awareness rating. It appears that these tools are primarily familiar to students with a greater interest in finance or prior exposure to Professional Platforms for Finance; however, other tools, such as TipRanks, Visualping, Dataminr, Sentieo, and similar tools had very low awareness ratings. Awareness ratings for each of these tools remained below 2% of the student population, showing that the majority of students have limited exposure to these types of tools. The Zacks Research Wizard platform did not receive any awareness rating at all, which would indicate that respondents had no exposure to this platform.

Table 4.2: Familiarity with AI-Powered Investment Tools

AI Investment Tools	Frequency (n)	Percentage (%)
Do not use any AI tools	116	54.5%
Moomoo Malaysia	79	37.1%
AI StockMaster (Malaysia)	13	6.1%
Eikon (Refinitiv, LSEG)	11	5.2%

Other AI Tools *(combined)*	**18**	**8.5%**

In Section B2, we analyzed the results from this survey concerning actual usage of AI investment platforms compared with level of familiarity to determine whether there was a gap between being familiar with something versus using it. The results indicate that although most students appear to be familiar with these investment platforms, only a small percentage of respondents reported using these platforms during the actual investment period in their lives. While Moomoo Malaysia received the highest number of responses (67.6%) from those who said they had used the platform, showing a significant presence within Malaysian university students, the second highest was the AI StockMaster platform, with just 23.9% reporting that they had utilized the platform to invest with; significantly lower than their corresponding familiarity rate. The usage of all other AI investment platforms was extremely low, with less than 3% of respondents who said they had used Bloomberg Terminal, DanelFin, FinChat.io, FinRobot, MarketSenseAI and other similar platforms and very negligible numbers of respondents reporting 0% usage of TipRanks, Visualping, Dataminr and Zacks Research Wizard. Roughly 0.5% of respondents state that they have never utilized any AI investment tool.

Overall, these results reveal that AI tool adoption among students is highly concentrated in just one or two mainstream platforms, while most AI-related investment technologies remain largely unfamiliar and unused. Students are aware of AI in finance, but meaningful engagement and practical experience with these tools are still very limited.

Table 4.3: Usage of AI-Powered Investment Tools

AI Investment Tools	Percentage (%)	Frequency (n)
Do not use any AI tools	67.6%	144
Moomoo Malaysia	23.9%	51
AI StockMaster (Malaysia)	3.8%	8
Other AI Tools (combined)	4.7%	10

Section B3 of the survey collected information from participants on how much investment experience each participant has had with an AI based investment/research tool. As noted above, most participants are very inexperienced with AI in terms of their investing and research activities, with 69.5% indicating that they have never had any investment experience using an AI based platform. Thus, it appears that a large number of students have yet to become familiar with AI for real trading or research. Another 24.4% of participants indicated they have less than one year of experience. This indicates that most of the current users are new users, who began using AI based products because they were becoming more aware of the presence of AI in the financial sector.

Only a handful of participants indicated that they had been using AI for investing and research for more than one year. Approximately 4.8% reported having between one and three years of experience, 1.0% between three and five years of experience, and 0.5% for longer than ten years. The above information supports the idea that most college students do not yet have a lot of hands-on experience using an AI based investment tool in their investing and research activities. While there are a few popular AI tools, such as Moomoo and AI StockMaster, that have a relatively high number of users, the average length of experience with these tools is limited at best.

Table 4.4: Investment Experience with AI-Based Tools

Investment Experience Level	Percentage (%)	Frequency (n)
None	69.8%	148
Less than 1 year	24.5%	52
1–3 years	4.7%	10
3 years and above	1.4%	3

4.1.2 Descriptive Statistics and Reliability Analysis

An average and standard deviation method were employed to compute a central tendency and dispersion analysis for every one of the 12 constructs. Each construct consisted of numerous items measured using a Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree", and therefore each participant's response was averaged together to create a composite. On average, the sample reported a moderately positive attitude towards AI investment tools. Specifically, Perceived Usefulness received the highest average value of 3.85 with a standard deviation of .64, indicating that respondents viewed these AI investment tools as being useful and are likely to improve their decision-making. Perceived Risk was also relatively high, with a mean of 3.81 with a standard deviation of 0.76, indicating that although respondents considered these AI investment tools to be useful, they remain concerned with the uncertainties and risks associated with this new technology.

In relation to other constructs that were rated somewhat below the maximum value, the Smartphone Self-Efficacy construct (Mean=3.63 SD=0.89), Quality of Internet and Website (Mean=3.62 SD=0.83) and Perceived Easy Use (Mean=3.61 SD=0.76) had relatively high means while Behavioural Intention (Mean=3.58 SD=0.82) had relatively high means. This suggests that the Participants believed that they were capable of using the mobile investment platform, that they believed that their online investment systems were of good quality and would be relatively easy to use AI tools, and that they indicated their willingness to adopt mobile investment technologies. As indicated by Means and Standard Deviation scores for Attitude Toward Using (Mean=3.64 SD=0.80), Confidence (Mean=3.50 SD=0.89), Subjective Norm (Mean=3.39 SD=0.87) and Social Influence (Mean=3.38 SD=0.88) it also indicates that all of these constructs demonstrate positive attitudes, somewhat credible levels of confidence, but lower levels of external social pressure that influence attitude.

Trust had the lowest overall mean score of 3.35 and standard deviation of 0.85, suggesting respondents have a level of uncertainty about the ability of AI to provide reliable investment decisions. Overall, the means of the responses were between 3.35 and 3.85, indicating moderate to moderately high agreement across the constructs. All constructs showed acceptable variability regarding standard deviation, with values ranging from 0.64 to 0.89 and similarly, no extreme variance was noted, thus showing an overall consistency among participants' perceptions of the constructs.

A total of twelve measurement scales were tested for reliability using Cronbach's alpha, which is widely used to determine the internal consistency of a given set of items within a construct. For most researchers, an alpha value of at least 0.70 will indicate that the scales were reliably measuring the construct in question. Based on the results of this study's test of reliability, all twelve constructs exhibited acceptable internal consistency. Both Perceived Usefulness and Perceived Ease of Use obtained high reliability coefficients (alpha = 0.857 and alpha = 0.856, respectively), indicating that respondents provided a stable level of agreement regarding these perceptions of AI tools.

All constructs assessed in this study (Social Influence, Awareness of Service, Smartphone Self-Efficacy, Quality of Internet and Website) were found to have high levels of internal consistency (alpha coefficients). While perceived risk, trust, confidence, attitude toward use, and subjective norms also showed acceptable levels of internal consistency (alpha coefficients), some constructs exceeded an alpha level of 0.90 (Social Influence and Awareness of Service) indicating a particularly strong correlation between measurements (items).

Since all constructs had an alpha coefficient greater than 0.85, many constructs were well above an alpha threshold of 0.90 (Subjective Norm), therefore removing any individual item would not have had a substantial influence on improving the reliability of the measurement scales. Findings support the conclusion that the measurement instruments developed to capture perceived usefulness, ease of use, social influence, awareness, self-efficacy, internet quality, website quality, perceived risks, trust, confidence, attitude and subjective norms to perform a behaviour of interest have excellent reliability. Such findings provide strong support for the utilization of the developed measurement instruments in future analyses and testing of hypotheses based upon collected data.

Table 4.5: Descriptive Statistics and Reliability Analysis for All Constructs

Construct	No. of Items	Mean	Standard Deviation	Cronbach's Alpha
Perceived Usefulness (PU)	4	3.85	0.64	0.86
Perceived Ease of Use (PEOU)	4	3.61	0.76	0.86
Social Influence (SI)	3	3.38	0.88	0.90
Awareness of Service (AOS)	4	3.58	0.86	0.88

Smartphone Self-Efficacy (SSE)	4	3.63	0.89	0.89
Quality of Internet & Website (QIW)	4	3.62	0.83	0.91
Perceived Risk (PR)	4	3.81	0.76	0.86
Trust (TR)	4	3.35	0.85	0.92
Confidence (CF)	4	3.50	0.89	0.92
Attitude Toward Using (ATU)	4	3.64	0.80	0.94
Subjective Norm (SN)	3	3.39	0.87	0.91
Behavioral Intention (BI)	4	3.58	0.82	0.90

4.2 Inferential Analyses

Inferential analysis was performed to draw conclusions about the broader population based on the responses obtained from the sample and to empirically test the research hypotheses developed in Chapter 2. In this study, inferential analysis comprised two main statistical procedures: correlation analysis and multiple regression analysis. Correlation analysis was conducted to examine the strength and direction of the relationships among the twelve constructs. Multiple regression analysis was then used to determine the predictive effects of the independent variables on the dependent variables according to the research framework.

The results of the preliminary analyses demonstrated that normality, linearity, homoscedasticity, multicollinearity, and autocorrelation were not violated in an unacceptable manner in relation to Multiple Linear Regression Assumptions. (refer to appendix B) Diagnostic analyses noted that the residuals were normally distributed, there was a linear and homoscedastic (constant variance) relationship between each of the four predictor variables and the dependent variable, and there was no multicollinearity (an issue of correlation between the predictor variables) present. Errors were shown to be independent. Therefore, it was appropriate to use regression analysis for the hypothesis tests, and the results of those tests could be interpreted reliably.

4.3 Regression Analysis

Multiple regression analyses were conducted to examine the predictive relationships outlined in Hypotheses H1 to H12. Each regression model utilized composite construct scores as independent variables to identify the extent to which they explained the variance in the respective dependent variables.

4.3.1 Determinants Of Perceived Usefulness (PU)

Analysis for multiple linear regression tests was conducted after determining whether or not the assumptions for regression were satisfied, through examination of a variety of tests, including linearity and homoscedasticity tests of the residuals and diagnostic tests for normal distribution of the residuals. Overall, no classifications of multicollinearity were noted in the multiple linear regression analysis, indicating that this regression model could be used effectively to investigate the hypotheses of interest.

The effects of Social Influence (SIC3) and Awareness of Service (ASC4) on Perceived Usefulness (PUC1) were evaluated using a multiple regression analysis. The two independent variables account for approximately 25.9% of the variance in perceived usefulness, as indicated by the analysis's R value of 0.508 and R-squared value of 0.259. Social Influence had a β of 0.238 ($t = 3.21$, $p = 0.002$) and Awareness of Service had a β of 0.330 ($t = 4.43$, $p < 0.001$), both of which were statistically significant predictors. These results imply that students are more likely to find AI-powered investment tools beneficial when they are more aware of these tools' capabilities and are influenced by their peers. Thus, hypotheses H2 and H8 are validated.

Table 4.6: Multiple Regression Results for Determinants of Perceived Usefulness (PU)

Model 1	Unstandardized Coefficients		Standardized Coefficients	t	p-value	Decision
	B	SE	Beta			
Constant	2.378	0.178	—	13.35	0	
Social Influence	0.175	0.054	0.238	3.207	0.002	H2 supported
Awareness of Service	0.248	0.056	0.33	4.434	0	H8 supported

Dependent Variable: Perceived Usefulness; SE=Std. Error

Note: $R^2 = 0.259$, Adjusted $R^2 = 0.251$, $F(2, 207) = 36.085$, $p < .001$

4.3.2 Determinants Of Perceived Ease of Use (PEOU)

The regression model with Perceived Ease of Use as the dependent variable included Smartphone Self-Efficacy and Quality of Internet and Website as predictors. The model achieved an R^2 value of 0.407 (Adjusted $R^2 = 0.401$), indicating that 40.7% of the variance in Perceived Ease of Use is explained by these two variables. Both predictors were significant: Smartphone Self-Efficacy ($\beta = 0.284$, $t = 4.27$, $p < 0.001$)

and Quality of Internet and Website (β = 0.328, t = 4.64, p < 0.001). These findings support H9 and H10, revealing that higher confidence in smartphone usage and better system quality lead students to perceive AI investment tools as easier to operate.

Table 4.7: Multiple Regression Results for Determinants of Perceived Ease of Use (PEOU)

Model 2	Unstandardized Coefficients		Standardized Coefficients	t	p-value	Decision
	B	SE	Beta			
Constant	1.389	0.191	—	7.272	0	
Smartphone Self-Efficacy	0.284	0.066	0.33	4.273	0	H9 supported
Quality of Internet Connection & Website	0.328	0.071	0.358	4.636	0	H10 supported

Dependent Variable: Perceived Ease of Use (PEOU); SE=Std. Error
Note: $R^2 = 0.407$, Adjusted $R^2 = 0.401$, $F(2, 207) = 71.005$, $p < .001$

4.3.3 Determinants Of Attitude Toward Using (ATT)

A comprehensive regression model was conducted to identify the determinants of Attitude Toward Using AI investment tools. Six variables were included—Perceived Usefulness, Perceived Ease of Use, Trust, Perceived Risk, Social Influence and Confidence—and the model yielded a high R^2 value of 0.751 (Adjusted $R^2 = 0.744$). This indicates that 75.1% of the variation in Attitude is explained collectively by these predictors.

Perceived Usefulness ($\beta = 0.274$, $t = 4.76$, $p < 0.001$), Trust ($\beta = 0.198$, $t = 4.10$, $p < 0.001$), Perceived Risk ($\beta = 0.122$, $t = 3.09$, $p = 0.002$), Social Influence ($\beta = 0.110$, $t = 2.65$, $p = 0.009$) and Confidence ($\beta = 0.490$, $t = 10.09$, $p < 0.001$) were all found to have significant positive effects on Attitude. Perceived Ease of Use, however, displayed a significant but negative coefficient ($\beta = -0.167$, $t = -3.26$, $p = 0.001$). These findings provide support for H1, H4, H5, H6 and H11, and partial support for H3, although the negative direction of the relationship may suggest suppression effects once other predictors are controlled. This indicates that students' attitudes are shaped most strongly by their confidence, perceived usefulness and trust, while perceived ease of use may play a more nuanced or indirect role.

Table 4.8: Multiple Regression Results for Determinants of Attitude Toward Using (ATT)

Model 3	Unstandardized Coefficients		Standardized Coefficients	t	p-value	Decision
	B	SE	Beta			
Constant	0.042	0.199	—	0.214	0.831	
Perceived Usefulness (PU)	0.296	0.058	0.24	5.131	0	H1 supported
Perceived Ease of Use (PEOU)	−0.159	0.052	−0.153	−3.075	0.002	H4 supported
Perceived Risk (PR)	0.114	0.04	0.108	2.848	0.005	H5 supported
Trust	0.223	0.048	0.239	4.653	0	H6 supported
Confidence	0.527	0.047	0.592	11.154	0	H11 supported

Dependent Variable: Attitude Toward Using; SE=Std. Error
Note: $R^2 = 0.743$, Adjusted $R^2 = 0.736$, $F(5, 204) = 117.784$, $p < .001$

4.3.4 Determinants Of Behavioral Intention (BI)

The final regression model examined the influence of Attitude and Subjective Norm on Behavioral Intention. The model achieved an R^2 value of 0.654 (Adjusted R^2 = 0.651), revealing that these two variables explain 65.4% of the variance in students' intention to use AI investment tools. Both Attitude ($\beta = 0.594$, $t = 9.84$, $p < 0.001$) and Subjective Norm ($\beta = 0.272$, $t = 4.94$, $p < 0.001$) were significant positive predictors. These findings fully support H7 and H12, confirming that students who hold favorable attitudes and perceive social approval or encouragement are more likely to intend to adopt AI-based investment technologies.

Table 4.9: Multiple Regression Results for Determinants of Behavioural Intention (BI)

Model 4	Unstandardized Coefficients		Standardized Coefficients	t	p-value	Decision
	B	SE	Beta			
Constant	0.494	0.16	—	3.093	0.002	
Attitude Toward Using	0.594	0.06	0.576	9.843	0	H7 supported
Subjective Norm	0.272	0.055	0.289	4.937	0	H12 supported

Dependent Variable: Behavioral Intention; SE=Std. Error

Note: $R^2 = 0.654$, Adjusted $R^2 = 0.651$, $F(2, 207) = 195.904$, $p < .001$

4.4 Discussion of Findings

4.4.1 Determinants of Perceived Usefulness (PU)

From the result of the first regression model, both Social Influence and Awareness of Service had a significant impact on UTAR students' Perceived Usefulness of AI-based tools for investment purposes. The positive association between Social Influence and Perceived Usefulness indicates that students perceive AI-

based tools to be useful due to receiving verbal or non-verbal encouragement, approval, or recommendations from friends, family, peers, and community groups. The results of this study indicate that the hypothesis of this model is supported by both the Theory of Reasoned Action and the Technology Acceptance Model 2.0. Supporting evidence from past research by Venkatesh and Davis (2000) shows that Social Influence plays an important role in increasing the user's Perceived Usefulness, particularly if the user has not previously used the technology, and when the user is relying on social cues to determine the perceived utility of a particular product. In a similar finding, Zhou et al. (2010), found that Mobile Financial Technology users would develop stronger perceptions of usefulness, when the technology is endorsed by trusted peers. This study demonstrates that a social approval mechanism influences the development of PU, and thus UTAR students develop their evaluations based on conversations with peers and their perceptions of the use of the tool by others.

Awareness of Service positively and significantly impacts perceived usefulness. When students understand the features of an investment tool, through both formal and/or informal channels, the higher their chance of seeing the usefulness of that investment tool. Previous studies have shown that awareness is an important factor when evaluating perceived usefulness of a system. If you don't know what something can do, you can't see how useful it is. Therefore, the studies of Lin and Lu (2000) and Curtin et al. (2013) state that increased awareness gives users a better understanding of how the system has practical advantages and therefore increases perceived usefulness. Furthermore, the literature review found that awareness is an external factor in the Technology Acceptance Model (TAM), which influences the perception of usefulness based on users' understanding of how the tool increases their efficiency or performance. The findings of Model 1 clearly indicate that when individuals are both given social support, as well as a good understanding of the AI investment tools' capabilities, their perceived usefulness will be greater than those who are not.

4.4.2 Determinants of Perceived Ease of Use (PEOU)

The second regression model indicates a positive association between Smartphone Self-Efficacy and the Quality of Internet/Website and the Perceived Ease of Use (PEOU). The fact that students who have more confidence in their ability to use a smartphone perceive AI investment tools as easier or less difficult to use supports the hypothesis. In previous literature, it has been shown that increasing Self-Efficacy reduces fear and encourages increased familiarity with the product and decreases perceived levels of difficulty. For example, Compeau and Higgins (1995) found that self-efficacy was a primary predictor of users' level of comfort with and ability to navigate through digital systems. Likewise, Hsiao and Tang (2015) researched mobile learning and found that users who are confident reported higher levels of ease with using their mobile devices for educational purposes than users who reported less confidence. The literature review you have conducted provides further evidence that students who have greater Digital Literacy experience fewer barriers to entry, require less assistance, and are less intimidated by using new applications. Accordingly, students who possess greater Digital Literacy naturally report having greater perceived ease-of-use.

The internet and website quality impacted positively on PEOU, because by providing stable technology performance together with fast loading times and a clear, easy-to-use interface, these two attributes typified less frustration resulting in increased usability. Support of this hypothesis further validates prior research conducted by Cyr et al. (2006) and Tan and Teo (2000) indicating the importance of quality systems for perception of ease-of-use, as a higher quality system requires less mental and physical effort to operate. As described within the literature review, system quality is an environmental influence on PEOU and is Interactively associated with how the user

interacts with, and how the user is lessened by obstacles and cognitive load when using a system; in a similar manner, using an intuitive interface coupled with a reliable network giving users of AI financial tools an easier time managing these systems, Model 2 established that both personal technological abilities and supportive environment are paramount in forming ease-of-use beliefs in young users.

4.4.3 Determinants of Attitude Toward Using (ATT)

The third regression model produced the greatest amount of explanatory power across all four regression models. The combined influence of Perceived Usefulness, Perceived Ease of Use, Perceived Risk, Trust and Confidence are a significant influence on students' Attitudes Toward Using AI investment tools. Students are likely to develop a favourable attitude when they view an AI tool as useful in their ability to enhance their investment performance, finance understanding, and decision-making efficiency. As such, the existing theory has been supported and reinforced, with the User Attitude being largely determined by perceived usefulness. Additional research conducted by Davis (1989) and Venkatesh & Davis (2000) has demonstrated the strength of the relationship between Perceived Usefulness and a user's evaluation and intention to use AI-based tools in different Digital Finance and fintech ecosystems.

There was an unexpected but statistically significant negative relationship between perceived ease of use (PEOU) and attitude after controlling for usefulness, trust, confidence and risk. In terms of our hypothesis, the evidence technically supports our prediction that there is a significant effect of PEOU on Attitude; however, the negative coefficient offers more of a complex interpretation. In financial situations, students may interpret an extremely easy-to-use tool to mean that there is not enough substance or depth within it to assist them in their financial decision-making process

indicating a weakness in the analytical capabilities of that tool (i.e., how to determine what to invest in). Consequently, they may also view a tool that is "too simple" (PEOU = high) to be less sophisticated or not very reliable for making serious investments (PEOU = low). Another potential explanation would be that the other variables (Confidence and Trust) are much stronger predictors of Attitude due to statistical suppression; when the variance of Confidence and Trust is removed from the model, then the remaining variance for PEOU will have a negative association with Attitude. Therefore, ease of use would be much less important than reliability, performance and assurance to increase positive evaluations in a highly risky investment domain.

Unexpectedly, perceived risk was found to be positively correlated with attitude. Even though the theory predicts a negative relationship, in this instance, students who were more aware of risks tended to be more engaged, knowledgeable, or practical when it comes to investing behaviours. In addition, since these students have a high level of confidence and trust in the service, their positive view of the tool continues even though they acknowledge the risks involved with utilizing it. This supports the current hypothesis and illustrates the complicated nature of AI-based finance. It demonstrates that being aware of the risks does not necessarily decrease an individual's inclination to adopt; rather, it depends on their understanding of the benefits and safeguards associated with adopting.

Trust and Confidence both exhibited strong positive effects on Attitude, with Confidence showing the largest standardized coefficient in the model. These findings support their respective hypotheses and are highly consistent with your literature review, which highlighted that financial technologies require psychological assurance for adoption. When students trust that the AI tool is transparent, reliable, and ethically designed, and when they feel confident in its ability to produce accurate and consistent outputs, they are far more likely to hold positive attitudes toward using it. Prior research

by McKnight et al. (2002) and Gefen et al. (2003) similarly emphasised the central role of trust in shaping fintech adoption. Confidence, in particular, is crucial because investment decisions carry uncertainty and potential financial loss. Students who feel secure and assured by the system form the most favourable attitudes. Overall, Model 3 demonstrates that attitudes are shaped less by simplicity and more by usefulness, trustworthiness, psychological assurance, and knowledgeable engagement.

4.4.4 Determinants of Behavioural Intention (BI)

The final regression analysis assessed how Attitude and Subjective Norm influenced Behavioural Intention to adopt AI investment tools. Findings revealed Attitude and Subjective Norm were significant and positively correlated with Behavioural Intention. Thus, when students evaluated the overall performance of AIT as good (Attitude) and perceived their peers' support for AIT use (Subjective Norm), students will be more likely to participate in using AIT. Findings supported the hypothesis and coincided with both Technology Acceptance Model and Theory of Reasoned Action, which both argue that favourable Attitudes will form one's willingness to perform an action. The literature review also indicated that when evaluating fintech, positive evaluations of usefulness, trustworthiness, and ease of use tend to lead to strong intentions to utilise. This conclusion aligned with the studies of Ajzen (1991), Chung et al. (2022), and Yin et al. (2023), where Attitudes were found to be one of the strongest predictors of fintech adoption intentions in young adults and those who utilise technology.

The results establish that Subjective Norm significantly influences the participants' intentions to use AI-based investment tools, which supports the hypothesis

and is consistent with the TRA and TPB theories that suggest social expectations are a major factor in determining people's intentions. The greater the perception by students that their family, friends, or lecturers think they should be using these tools, the greater their intention to utilize them; this is particularly true in the case of university students where academic culture and influence of peers through social media have a greater impact on financial attitude than most other types of expectations. Previous research in this area has indicated that young investors are highly influenced by their peers, their authority figures, and online communities when determining their normative beliefs regarding the adoption of fintech products. Therefore, all the variables in Model 4 confirm that students' intentions towards the use of AI-based investment tools are determined by Attitude (Personal Evaluation) and Subjective Norm (Social Expectation).

4.5 Conclusion

This chapter presented the data analysis and empirical findings of this study. From the descriptive analysis, it emerged that the sample is mostly composed of younger UTAR students, slightly dominated by females, at undergraduate levels with below-average investment experience. The central tendencies of the constructs indicate a moderate to moderately high range for perceived usefulness, ease of use, awareness, trust, confidence, attitude, and intention toward AI-based investment tools.

The reliability analysis revealed that all constructs had internal consistency with Cronbach's alpha values above 0.85 for each scale, hence validating the suitability of the measurement instruments for inferential analysis.

The inferential analyses provided empirical evidence to support most of the hypothesized relationships that have been derived from the extended TAM and TRA framework. Perceived ease of use, awareness of service, smartphone self-efficacy, and quality of Internet/Website significantly influence perceived usefulness and perceived ease of use. Meanwhile, attitude toward AI-based investment tools is largely influenced by perceived usefulness, trust, perceived risk, social influence, and, above all, confidence. Behavioural intention is primarily influenced by attitude and subjective norm, indicating the combined importance of personal evaluation and social expectations in the adoption of the AI-based investment tool among UTAR students.

Chapter 5 will discuss these findings in the light of past literature, elaborate on the implications both at a theoretical and practical level, highlight the limitations of this study, and provide recommendations for future research and industry practice.

Table 4.10: Summary Of Hypothesis Testing

Hypothesis	Result
H1: Social Influence has a significant effect on Perceived Usefulness	**Supported**
H2: Awareness of Service has a significant effect on Perceived Usefulness	**Supported**
H3: Smartphone Self-Efficacy has a significant effect on Perceived Ease of Use	**Supported**
H4: Quality of Internet and Website has a significant effect on Perceived Ease of Use	**Supported**
H5: Perceived Usefulness has a significant effect on Attitude Toward Using	**Supported**
H6: Perceived Ease of Use has a significant effect on Attitude Toward Using	**Supported**
H7: Perceived Risk has a significant effect on Attitude Toward Using	**Supported**
H8: Trust has a significant effect on Attitude Toward Using	**Supported**
H9: Confidence has a significant effect on Attitude Toward Using	**Supported**
H10: Attitude Toward Using has a significant effect on Behavioural Intention	**Supported**
H11: Subjective Norm has a significant effect on Behavioural Intention	**Supported**

Chapter 5: Conclusion and Implications

5.0 Introduction

The main objectives of this research are reviewed in this chapter, along with a summary of the statistical results presented in Chapter 4. Constructs from the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA) and other related variables that were used to identify the factors that influence university students' intention to use AI-based investment or research tools, form part of the basis for the statistical findings listed in Chapter 4, which are discussed in close detail in this chapter through descriptive statistics, reliability analysis, correlation and regression reports that demonstrate how individual factors correlate with students' perceptions, attitudes, and suggestions of using AI-based investment or research tools. The chapter will also outline the practical significance of these findings for fintech developers, educators, universities, and policymakers. Additionally, a list of limitations of the study will also be included, along with recommendations for future research.

5.1 Summary of Statistical Analyses and Major Findings

The results suggest that while students may not yet be using AI-based investment tools, they do perceive AI as an attractive technology. Whilst a few of the participants were familiar with investment platforms such as Moomoo, AI StockMaster and Maybank Assist, most of them did not have substantial experience in using these platforms to make actual financial decisions, thus highlighting the nascent stage of AI technology adoption for university students. Central tendency analyses further demonstrated that students exhibited moderate levels of trust in and confidence in AI

as a tool for financial management, and moderate levels of perceived ease of use. Therefore while students recognise some of the benefits of AI, a majority do not feel comfortable relying on an AI-generated recommendation for financial decisions.

Reliability analysis confirmed strong internal consistency across all factors; thus, the items measured were determined to provide a comprehensive representation of the constructs. Correlation analyses also demonstrated a strong positive correlation across all variables, especially for the measures of confidence, trust, attitude, and behavioural intention, thereby supporting contemporary studies, which emphasise the importance of psychological literature in terms of how and why users adopt emerging technologies.

All hypotheses were supported by regression analyses, which demonstrate that the level of perceived ease of use, awareness of AI features and how easily they can be navigated are both significant predictors of perceived usefulness of AI tools. Therefore, when students have a good understanding of the features and can easily navigate through them, they will view the AI tools as more useful to them. Regression analyses indicated that smartphone self-efficacy and system quality are important predictors of perceived ease of use; therefore, the greater one's digital confidence, and access to reliable technology, the more likely one is to perceive an AI tool as usable. Regression analyses also showed that the following factors all had a statistically significant effect on attitude toward using AI tools: perceived usefulness, trust, confidence, social influence, and perceived risk; however, it was confidence that had the strongest impact. Thus, it is critical for students to believe that they can effectively utilise an AI system, as this will ultimately determine their attitude toward using one. Finally, both attitude and subjective norm were significant predictors of behavioural intention to use AI tools. This is consistent with the Theory of Reasoned Action which suggests that an individual's evaluation and the social pressure placed on them will determine their behavioural choices. Overall, results of this study support the conclusion that the

extended Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA) demonstrate a comprehensive and effective explanation of AI adoption behaviour by university students.

5.2 Managerial Implications of the Study

5.2.1 Implications for FinTech Developers

According to the study results, research participants demonstrated that confidence, perceived value of technology, and perceived trust are the strong predictors of the students' attitudes and behavioral intentions to use financial technology tools. Developers need to improve users' sense of control, security and trust while using financial technology tools. To do this, developers should include a guided onboarding process, create basic learning resources, and give users a clear understanding of the logic behind any AI-generated recommendations. The clearer users are about how the system produces a recommendation to invest, the more confident they will become about using the automated tools, resulting in increased confidence in their investment decision-making.

The average score of the perceived usefulness scale was higher than any of the other scales. This indicates that students recognise the potential positive impacts of utilising AI-based platforms in their investment activities. The developers should demonstrate the value of AI-based tools for real-time analysis of data, management of portfolios, screening for stocks, and tools for supporting users' learning. By demonstrating these benefits early to students, they will have a greater likelihood of continued use and engagement with the platform.

The perception of how easy it is to use a platform has an important relationship with many other aspects of the model, but it also has a negative correlation with the student's preference for a simple appearance of the platform. When the platform has a simple appearance, the student has concerns about the credibility and reliability of the platform. Developers need to find a balance between an easy-to-use platform and providing advanced features through the platform. The platform should be easy to use; however, it should also offer advanced analytics capabilities and perform reliably. Many students utilize mobile devices to access information; therefore, the platform should be optimized to allow for easy mobile access, quick load times, reliable performance, and compatibility with various types of mobile devices.

Trust was rated the lowest in the study. Developers will need to address the concerns regarding the level of trust that students have in the platform by providing information regarding the functioning of the AI, outlining the potential risks involved in using the AI platform, disclosing compliance with regulatory practices, and explaining how to protect user data. Trust can be built through a level of transparent communication between the developer and the user. If users feel that their financial decisions and personal information are protected by reliable technology, they will likely accept AI-based investing as a trusted and dependable investing tool.

5.2.2 Implications for Educators and Universities

Collaboration between universities and FinTech companies can further improve learning outcomes. Industry-led workshops, student-access trial accounts on real digital platforms, academic–industry seminars, and internship opportunities can provide early

exposure to the technology as used in real market settings. Such initiatives not only improve digital competence but also contribute to the development of future-ready graduates who are confident using AI responsibly within the financial environment.

5.2.3 Implications for Policymakers and Financial Regulators

There are two distinct findings regarding the influence of students' perceptions of AI investment tools on technology readiness and likelihood to engage with AI-based recommendations; however, the main finding reveals that while students express interest in AI as it relates to investing or as investment tools, most lack meaningful practical use of them, so they are unsure how to fully use the recommendations provided by AI-driven applications. Thus, universities must be proactive in preparing students for future uses of technology by creating learning environments designed to support technological readiness. Students gain a greater level of confidence and familiarity regarding the operation of AI in making financial decisions through the use of AI-driven trading systems in simulated settings as part of their educational experience such as hands-on activities, coursework. Through this kind of structured exposure to the technology, students can gain a greater level of confidence regarding automation and their anxiety toward automation will decrease, resulting in the increased likelihood that they will view AI as having a greater level of usefulness and ease-of-use.

Another area in which universities must help students develop their understanding of digital financial literacy that relates to risk, is with the Perceived Risk construct. Perceived Risk is an area in which findings indicate that students perceive their awareness of uncertainty, however students will benefit from additional guidance

for evaluating and managing risk. Classroom educators should make an effort to integrate topics such as volatility, market uncertainty, ethical issues that arise from automated decision making, algorithmic bias, data protection, cybersecurity threats, and fraud related to technology into their classroom discussions to ensure that students do not overly depend on AI for decision making but instead learn how to evaluate the information provided by AI in a responsible manner.

These results provide valuable information for policy makers and regulators. Students indicated an intent to use AI tools only in conjunction with established governance structures, specifically those that provide safety nets with respect to factors including: fairness; data protection; accountability for errors; security of users. Students indicated an intent to use AI tools only in conjunction with established governance structures, specifically those that provide safety nets with respect to factors including: fairness; data protection; accountability for errors; security of users. Regulators must increase their supervision of AI-powered Trading Apps to satisfy the unease of the student body through establishing guidelines in accordance with ethical standards, privacy policies, and the mandate for transparency on how an individual receives Investment Advice through AI, as well as the Management of Risk and the Mechanism for Protection against Potential Losses when utilizing AI systems made available to them.

By establishing National Programs to improve Digital Literacy among the youth, countries can provide students with the ability to be responsible users of Technology. Students should know how to differentiate between authentic Digital Platforms, identify red flags associated with online scams, and effectively manage Financial Risks; thus, creating a greater sense of confidence when utilizing new Financial Technologies. Regulated educational environments like the AI Trading Sandbox regulated by the Securities Commission of Malaysia create a safe environment

where Students may experiment with AI Trading Tools without the risk of incurring any Financial Losses.

To develop clear guidance on the ethical use of Artificial Intelligence (AI) and collaborative partnerships with other Blockchain technologies, Regulations should develop a plan with Institutions of Higher Learning and Financial Technology (Fintech) Associations for establishing. Through involvement in the development of Regulations around AI, this may provide students a greater degree of confidence to use AI tools for Financial Investments. It may establish an environment that can be used to establish transparency, accountability, and legal protections for users in a financial context.

5.2.4 Implications for the FinTech Ecosystem

The conclusion of the study shows that all the hypotheses were supported, leading to support for the extended TAM-TRA framework that states that technological readiness, usability, and social influence affect the willingness of students to invest in the technology of AI. In other words, to successfully implement a technology investment, the FinTech ecosystem must come together collaboratively, rather than relying on isolated actions from individual stakeholders. Therefore, developers are responsible for providing improved levels of platform performance, visibility of usefulness and user trust. Universities also have a responsibility to ensure that students are adequately equipped with hands-on experience and digital finance literacy. Regulators are responsible for ensuring that the governance and protection structures are in place to protect young investors from algorithmic uncertainty and market risk.

Through the collective efforts of the three primary actors, Malaysia can develop a new generation of investors who are digitally capable and confident when making investment decisions using technology. The ecosystem must provide students with the tools to be active participants in their investment decisions by equipping them with the knowledge to analyse, compare, and critically evaluate AI-generated investment intelligence. The synergies formed through this investment approach will enable a rapid increase in the adoption of digital investment across the country, leading to the development of a more sophisticated, responsible, and innovative financial services industry.

5.3 Limitations of the Study

The drawbacks of this study, although there are valuable insights, need to be discussed:

1. The research was only conducted among UTAR students and, therefore, it is limited in its ability to generalize to the broader population, such as working adults, seasoned investors, and other educational experiences.
2. A self-administered survey was utilised to conduct the research, and participants' answers could be affected by response bias such as social desirability, misinterpretation of questions, and distraction during survey completion.
3. Most respondents did not have prior experience using AI-based investment tools; therefore, their responses were based on their beliefs rather than on their actual experience with using the tools. Thus, the results may be less relevant to experienced users of these tools.
4. The research was a cross-sectional study and used only one point in time to capture respondents' perceptions. The results, therefore, did not capture any changes in attitude or intention as respondents gained experience or experienced financial risk or observed how AI performed over a period.

Even though this research has limitations, the results are not rendered invalid; instead, they point to future research that will improve and expand our knowledge of how AI is used in financial decision-making.

5.4 Recommendations for Future Research

Increasing generalisability in future research may be enhanced by recruiting participants from multiple universities or workplaces or having active retail investor customers. A more representative sample will provide greater insight into how different groups of people view and accept AI technology. Longitudinal designs will enable researchers to follow how users' behaviour towards this new technology changes as users become more familiar with A.I. tools and as the algorithms associated with them continue to evolve. In addition to using the constructs identified above, future studies should look into relating these constructs with AI literacy, perceived transparency, trust in regulators, algorithmic fairness, and financial anxiety. Each of these constructs could have implications for the acceptance of AI investment tools when there is a risk of losing money. Qualitative approaches, such as informal discussions with subjects through interviews or focus groups, could produce additional insights into how people's feelings and experiences impact their behavioural intentions to use AI tools that quantitative measures do not. Cross-country comparisons can help researchers determine if cultural differences affect individuals' perceptions of trust, risk, and technology adoption and therefore, may provide a basis for developing a global perspective regarding investment acceptance.

5.5 Conclusion

This research examined factors that affect how UTAR students accept AI-based investment tools, using an integrated TAM–TRA model with added psychological, social, and technological factors. Evidence suggests that students' acceptance of such tools is determined by their perceived usefulness, ease of use, trust, confidence, risk, and social influence; as well as by how they perceive themselves to behave about them and how society perceives their behaviour toward these products.

Thus, the study has added to the increasing body of literature regarding the acceptance of fintech and has offered practical insight for the developers, educators, and regulators trying to foster responsible usage of AI investment technologies by youth. Although there are some limitations to this study, it has laid a solid groundwork for future studies to follow and highlight the requirements for designing AI tools that are transparent, trustworthy, and easy to use as well as provide social support for using them.

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APPENDIX

Appendix A -Survey Questionnaire

UNIVERSITI TUNKU ABDUL RAHMAN

Faculty of Accountancy and Management

ANTECEDENTS OF UNDERSTANDING THE INVESTORS' ACCEPTANCE OF ARTIFICIAL INTELLIGENCE

I am currently pursuing my Bachelor of Degree Financial Technology at Universiti Tunku Abdul Rahman (UTAR). I am conducting research on antecedents of understanding the investors' acceptance of artificial intelligence. The aim of this study is [objective of the study for example, to gain new insights on the factors contributing to turnover intention of knowledgeable academics of students study at University Tunku Abdul Rahman (UTAR). This study is approved by UTAR Scientific and Ethical Review Committee, Ref No. : U/SERC/78-615/2025

I will be very grateful if you can spare 10 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.

Regards,

Yoong Shi Qi (Student ID: 2204498) Email: qiqiyoong2@1utar.my

Assoc Prof. Dr Sia Bik Kai, Email: siabk@utar.edu.my

Section A: <u>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+

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
17. Other, please specify _____

A4: Education Level

1. Foundation
2. Undergraduate
3. Master's Degree
4. Doctorate/PhD

A5. 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: <u>Basic Information on Perceptions of AI- Based Investment Tools</u>

Definition of Term

Perceptions of AI investment tools refer to investors' overall beliefs, attitudes, and judgments about the usefulness, trustworthiness, and potential risks of adopting AI-driven platforms, such as robo-advisors and algorithm-based trading systems, for financial decision-making. These perceptions are shaped by how investors evaluate the tools' efficiency, accuracy, ease of use, and transparency, as well as by concerns about reliability and loss of human control, ultimately influencing their intention to adopt such technologies.

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.
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 _____

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 slightly	Neutral	Agree slightly	Strongly Agree
A	**Perceived Usefulness**					
1.	Using AI-based investment tools improves my investment performance.	1	2	3	4	5
2.	AI-based tools make it easier to make investment decisions.	1	2	3	4	5
3.	AI-based tools enhance my productivity in managing investments.	1	2	3	4	5
4.	AI-based tools are useful in my investment activities.	1	2	3	4	5
B	**Perceived Ease Of Use**					
5.	Learning to operate AI-based investments tools is easy for me.	1	2	3	4	5
6.	It is easy for me become skillful at using AI-based investment tools.	1	2	3	4	5
7.	I find AI-based investment tools easy to use.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree slightly	Neutral	Agree slightly	Strongly Agree
8.	Interacting with AI-based investment tools does not require much mental effort.	1	2	3	4	5
C	**Social Influence**					
9.	People who influence my behaviour think I should use AI-based investment tools.	1	2	3	4	5
10.	People whose opinions I value prefer that I use AI-based investment tools.	1	2	3	4	5
11.	People important to me recommend the use of AI-based investment tools.	1	2	3	4	5
D	**Awareness Of Service**					
12.	I am aware that AI-based investment tools are available for use.	1	2	3	4	5
13.	I know about the features of AI-based investment tools.	1	2	3	4	5
14.	I am aware of the benefits of using AI-based investment tools.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree slightly	Neutral	Agree slightly	Strongly Agree
15.	I know where to access AI-based investment tools.	1	2	3	4	5
E	**Smartphone Self-Efficacy**					
16.	I am confident in my ability to download and install AI-based investment apps on my smartphone.	1	2	3	4	5
17.	I can troubleshoot common smartphone issues when using investment tools.	1	2	3	4	5
18.	I can learn how to use new investment apps without help.	1	2	3	4	5
19.	I can use smartphone features to optimize my investment activities.	1	2	3	4	5
F	**Quality of Internet & Website**					
20.	The internet connection I use for AI-based investment tools is stable.	1	2	3	4	5
21.	The website/app for AI-based investment tools loads quickly.	1	2	3	4	5
22.	The layout of the website/app is clear and easy to navigate.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree slightly	Neutral	Agree slightly	Strongly Agree
23.	The website/app provides smooth interaction without errors.	1	2	3	4	5
G	**Perceived Risk**					
24.	Using AI-based investment tools could cause me to lose money.	1	2	3	4	5
25.	I am concerned about the security of my personal data when using AI-based investment tools.	1	2	3	4	5
26.	I am worried that my information could be misused by AI-based investment tools.	1	2	3	4	5
27.	Using AI-based investment tools involves too much uncertainty.	1	2	3	4	5
H	**Trust**					
28.	I trust AI-based investment tools to perform reliably.	1	2	3	4	5
29.	I believe AI-based investment tools protect my best interests.	1	2	3	4	5
30.	AI-based investment tools are trustworthy.	1	2	3	4	5

No	Statement	Strongly disagree	Disagree slightly	Neutral	Agree slightly	Strongly Agree
31.	AI-based investment tools provide accurate information.	1	2	3	4	5
I	**Confidence**					
32.	I am confident that I can successfully use AI-based investment tools.	1	2	3	4	5
33.	I feel certain that I can make sound decisions using AI-based investment tools.	1	2	3	4	5
34.	I can rely on my own judgment when using AI-based investment tools.	1	2	3	4	5
J	**Attitude Toward Using**					
35.	Using AI-based investment tools is a good idea.	1	2	3	4	5
36.	I have a positive attitude towards AI-based investment tools.	1	2	3	4	5
37.	Using AI-based investment tools is beneficial.	1	2	3	4	5
38.	I like the idea of using AI-based investment tools.	1	2	3	4	5
K	**Subjective Norm**					
39.	People important to me would approve of my	1	2	3	4	5

No	Statement	Strongly disagree	Disagree slightly	Neutral	Agree slightly	Strongly Agree
	using AI-based investment tools.					
40.	People whose opinions I value support my use of AI-based investment tools.	1	2	3	4	5
41.	My peers think I should use AI-based investment tools.	1	2	3	4	5
L	**Behavioural Intention**					
42.	I intend to use AI-based investment tools in the future.	1	2	3	4	5
43.	I will regularly use AI-based investment tools.	1	2	3	4	5
44.	I will recommend AI-based investment tools to others.	1	2	3	4	5
45.	I plan to explore more features of AI-based investment tools.	1	2	3	4	5

Thank You for Your Participation

Appendix B -SPSS output

Regression Analysis Table -Model 1

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.9244	4.4913	3.8548	0.32794	210
Residual	-1.74133	1.78081	0.00000	0.55539	210
Std. Predicted Value	-2.837	1.941	0.000	1.000	210
Std. Residual	-3.120	3.191	0.000	0.995	210

a. Dependent Variable: PERCEIVED USEFULNESS C1

Regression Analysis Table -Model 2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.2473	4.4504	3.6083	0.48755	210
Residual	-1.78628	2.67071	0.00000	0.58864	210
Std. Predicted Value	-2.792	1.727	0.000	1.000	210
Std. Residual	-3.020	4.515	0.000	0.995	210

a. Dependent Variable: PERCEIVED EASE OF USE C2

Regression Analysis Table -Model 3

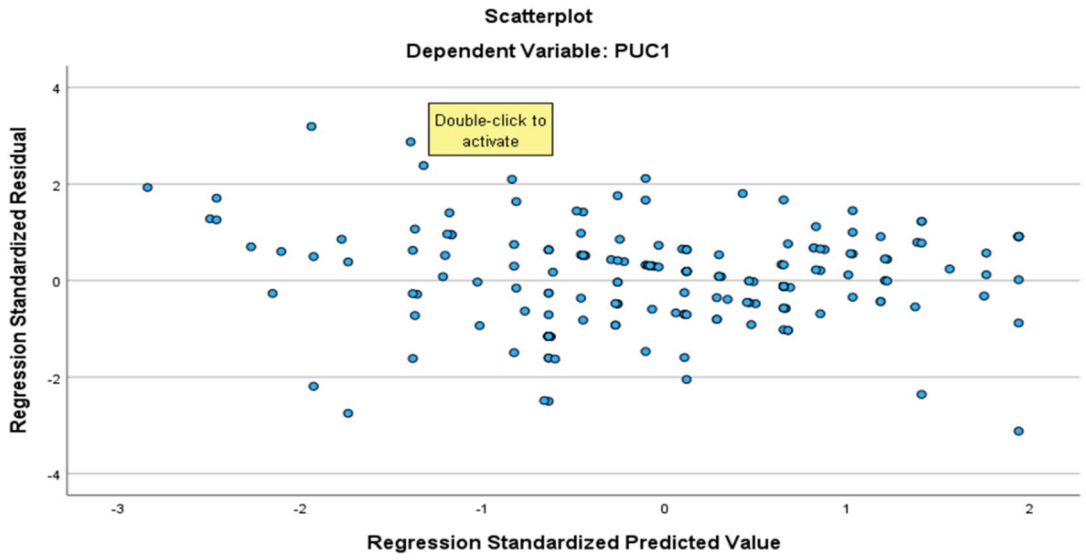
Residuals Statistics[a]					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.7685	5.0483	3.6357	0.68589	210
Residual	-1.37146	1.59767	0.00000	0.40368	210
Std. Predicted Value	-2.722	2.060	0.000	1.000	210
Std. Residual	-3.356	3.910	0.000	0.988	210

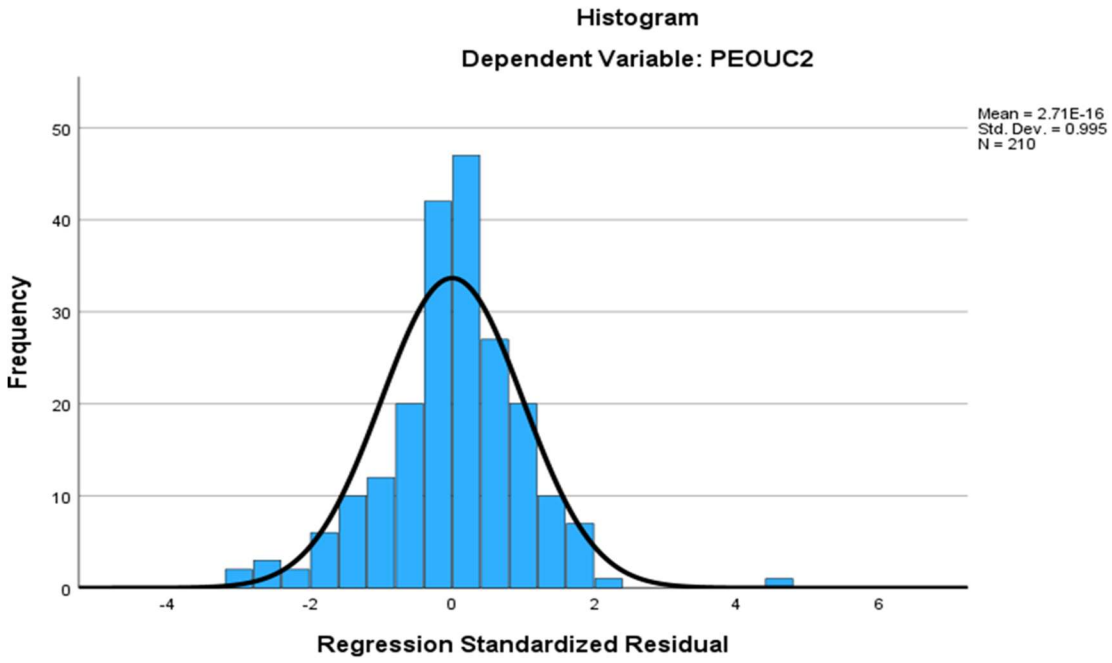
a. Dependent Variable: ATTITUDE TOWARDS USING C10

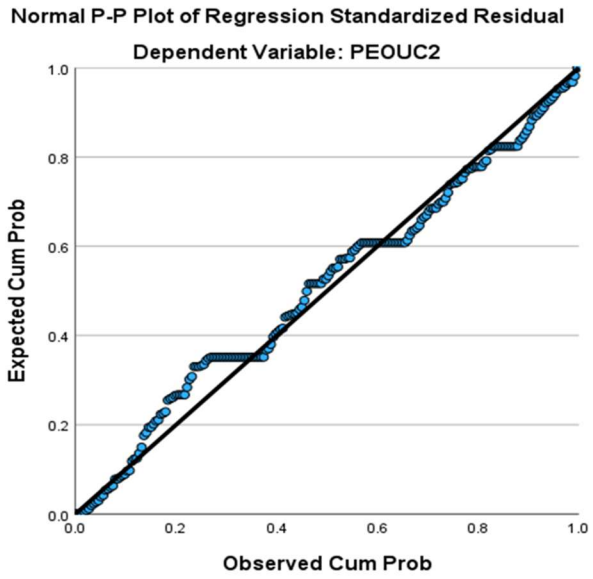
Regression Analysis Table -Model 4

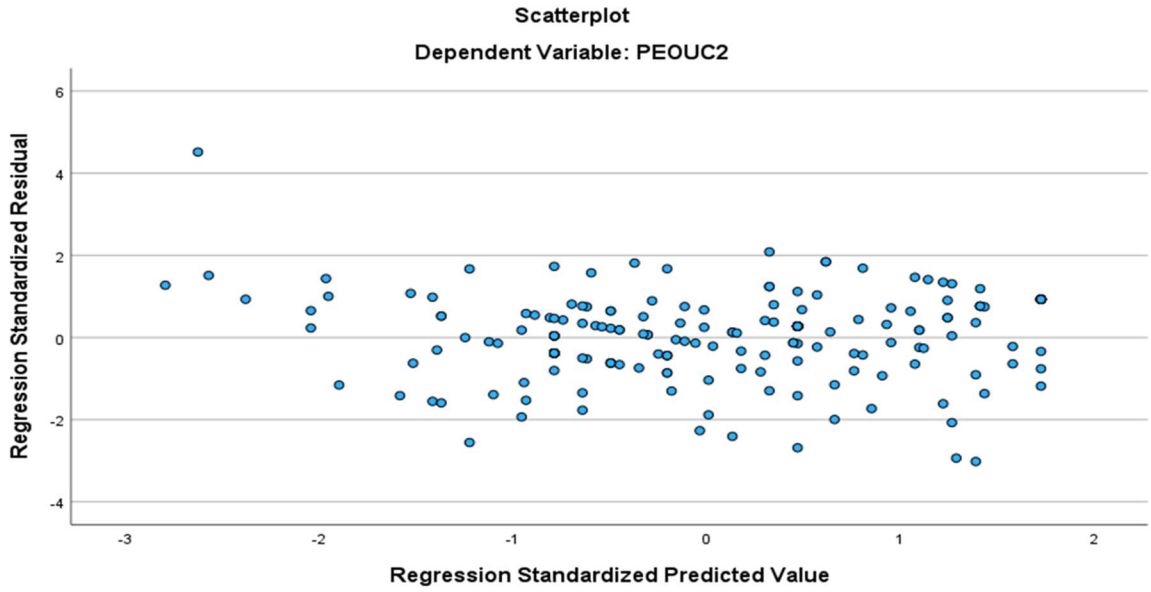
Residuals Statistics[a]					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.3598	4.8247	3.5762	0.66359	210
Residual	-2.39263	1.90096	0.00000	0.48233	210
Std. Predicted Value	-3.340	1.881	0.000	1.000	210
Std. Residual	-4.937	3.922	0.000	0.995	210

a. Dependent Variable: BEHAVIORAL INTENTION C12


Scatterplot
Dependent Variable: PUC1
Double-click to activate
Regression Standardized Residual
Regression Standardized Predicted Value
4
2
0
-2
-4
-3
-2
-1
0
1
2


Histogram
Dependent Variable: PEOUC2
Mean = 2.71E-16
Std. Dev. = 0.995
N = 210
Frequency
Regression Standardized Residual
50
40
30
20
10
0
-4
-2
0
2
4
6


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: PEOUC2
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: PEOUC2
Regression Standardized Residual
Regression Standardized Predicted Value
6
4
2
0
-2
-4
-3
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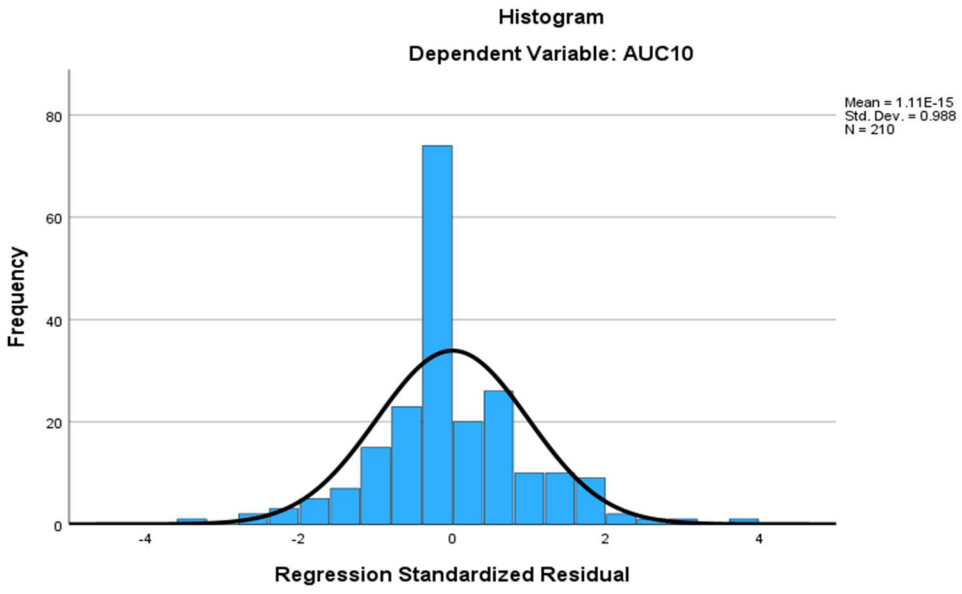
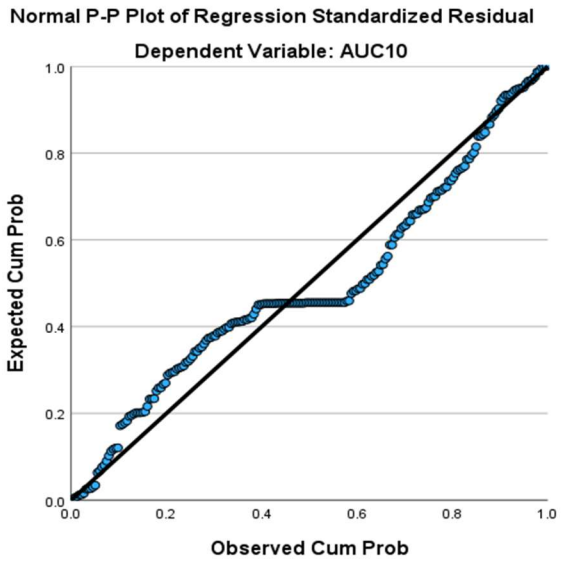
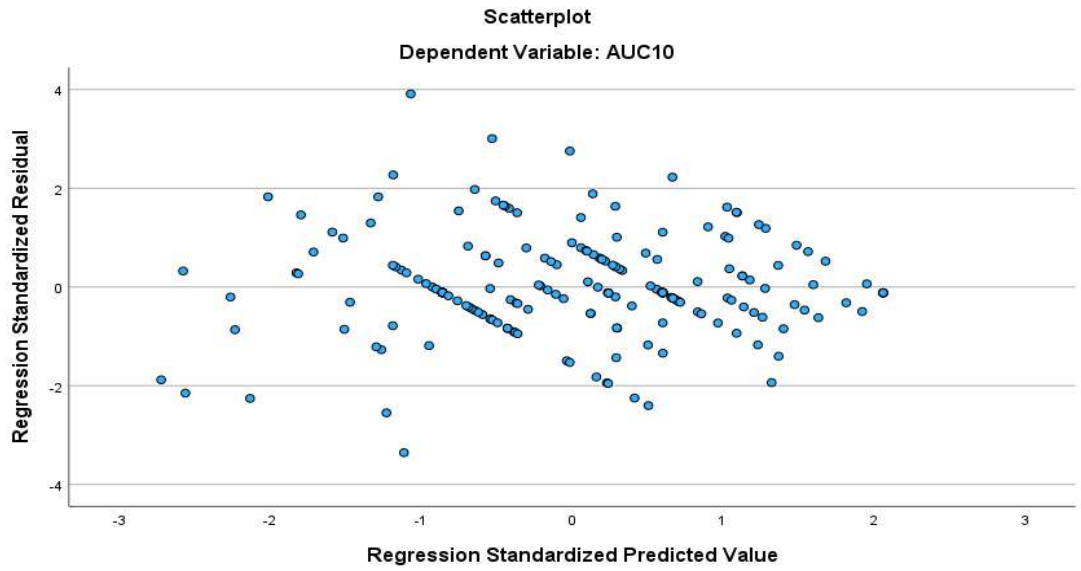
-1
0
1
2


Histogram
Dependent Variable: AUC10
Mean = 1.11E-15
Std. Dev. = 0.988
N = 210
Frequency
80
60
40
20
0
-4
-2
0
2
4
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: AUC10
Expected Cum Prob
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Observed Cum Prob


Scatterplot
Dependent Variable: AUC10
Regression Standardized Residual
Regression Standardized Predicted Value
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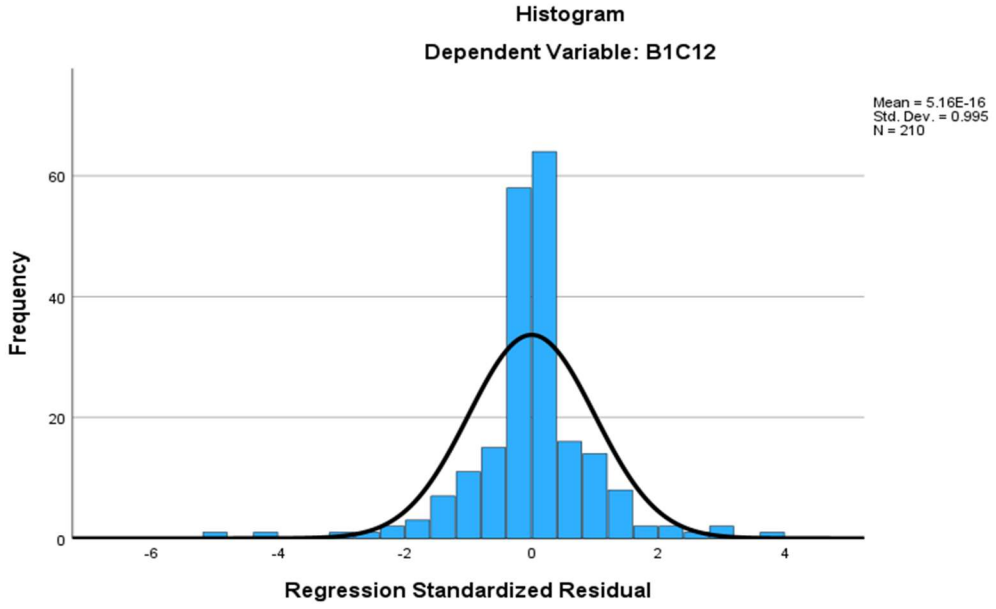
2
0
-2
-4
-3
-2
-1
0
1
2
3


Histogram
Dependent Variable: B1C12
Mean = 5.16E-16
Std. Dev. = 0.995
N = 210
Frequency
Regression Standardized Residual
60
40
20
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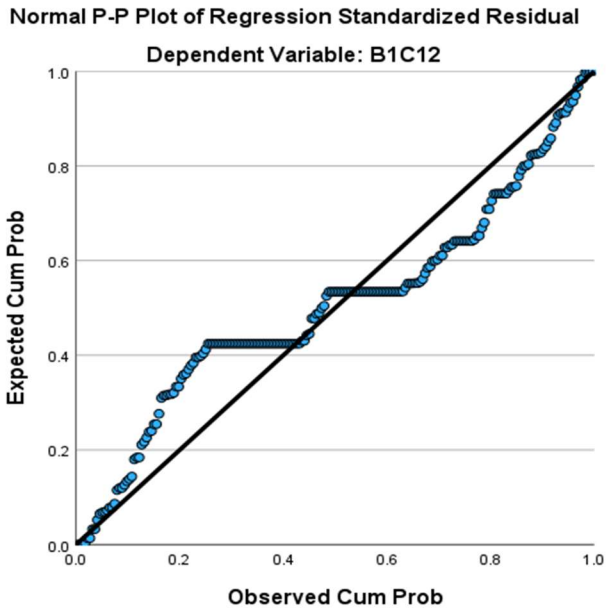
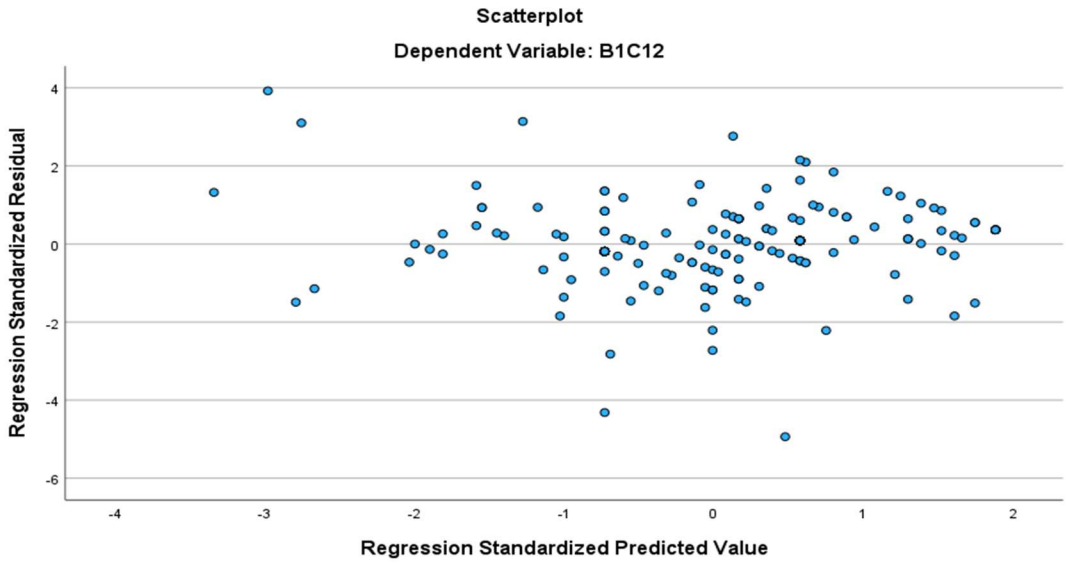
-6
-4
-2
0
2
4


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: B1C12
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: B1C12
Regression Standardized Residual
Regression Standardized Predicted Value
4
2
0
-2
-4
-6
-4
-3
-2
-1
0
1
2