AGENTIC AI ATTRIBUTES IN HEDONIC, HEURISTIC, UTILITARIAN, AND SYSTEMATIC PROCESSES: THE ROLE OF TRUST IN SHAPING USER ACCEPTANCE OF AGENTIC AI ROBO-ADVISORY

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DECLARATION

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AN	Anthropomorphism
ASB	Amanah Saham Bumiputera
ASNB	Amanah Saham Nasional Berhad
AT	Affective Trust
B40	Bottom 40% Income Group
BFSI	Banking, Financial Services, and Insurance
CNN	Convolutional Neural Network
CT	Cognitive Trust
FN	Functional
f^2	Effect Size
Gen Z	Generation Z
HSM	Heuristic–Systematic Model
HTMT	Heterotrait–Monotrait Ratio
IN	Informational
NLP	Natural Language Processing
PB	Perceived Benefit
PK	Perceived Knowledge

PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modelling
PP	Perceived Pleasure
Q^2	Predictive Relevance
R^2	Coefficient of Determination
TAM	Technology Acceptance Model
UA	User Acceptance
UTAUT	Unified Theory of Acceptance and Use of Technology
XAI	Explainable Artificial Intelligence

Preface

Despite the growing adoption of robo-advisory platforms, user acceptance remains a critical challenge, particularly in high-risk and trust-sensitive domains such as financial decision-making. While prior studies have explored technology adoption and trust in AI systems, limited research has examined how specific Agentic AI attributes influence user trust through different cognitive and emotional processing routes. In addition, the role of users' risk tolerance, especially among younger generations has not been sufficiently addressed in existing literature.

This research project was undertaken to investigate how Agentic AI attributes, expressed through hedonic, heuristic, utilitarian, and systematic processing, shape affective and cognitive trust, and how these trust dimensions influence user acceptance of Agentic AI robo-advisory services. The study adopts the Heuristic–Systematic Model (HSM) as its theoretical foundation and focuses on Generation Z users in Malaysia, a digitally literate group with growing exposure to AI-driven financial technologies.

It is hoped that the findings of this study will contribute to the academic understanding of trust formation in Agentic AI systems and provide practical insights for fintech developers, financial institutions, and policymakers in designing more transparent, trustworthy, and user-centric robo-advisory platforms. Ultimately, this research aims to support the responsible and effective adoption of Agentic AI in the evolving financial services landscape.

Abstract

The rapid rise of Agentic Artificial Intelligence (AI) has transformed financial technology by enabling robo-advisory systems that provide autonomous, adaptive investment guidance. Despite these advances, user acceptance remains contingent on trust, particularly within high-stakes financial investment decision-making. This study investigates how agentic AI attributes, expressed through hedonic, utilitarian, and systematic processing, shape affective and cognitive trust in robo-advisors, leading to user acceptance. Furthermore, this study examines respondents' risk tolerance to uncover behavioral patterns that shape the acceptance of agentic AI robo-advisors. Guided by the Heuristic–Systematic Model (HSM), this study adopts a positivist philosophy and employs a deductive and quantitative approach.

The rapid rise of Agentic Artificial Intelligence (AI) has changed financial technology by allowing robo-advisory systems to provide automated and adaptive investment guidance. However, user acceptance still depends on trust because financial investment decisions involve high risk. This study examines how agentic AI attributes, shown through hedonic, heuristic, utilitarian, and systematic processing, shape affective and cognitive trust in robo-advisors and lead to user acceptance. In addition, this study looks at respondents' risk tolerance to identify behavior patterns that influence the acceptance of agentic AI robo-advisors. This study is based on the Heuristic–Systematic Model (HSM) and uses a positivist philosophy with a deductive and quantitative approach. Data collected via a cross-sectional survey targeted Generation Z (ages 18–28) in Malaysia.

With 273 responses obtained and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM), the results confirm that Perceived Pleasure and Anthropomorphism have a significant impact on effective trust. Meanwhile, except for functional, Informational, Perceived Knowledge, and Perceived Benefit were found have a significant impact on Cognitive Trust. It also confirmed that affective and cognitive trust lead to acceptance of robo-advisory use. This research contributes theoretically by clarifying the dual roles of affective and cognitive trust in shaping the adoption of Agentic AI robo-advisors, and practically by guiding fintech firms and policymakers in designing transparent, user-centred financial AI systems.

CHAPTER 1: INTRODUCTION

1.0 Introduction

This chapter describes the evolution of Agentic AI, describing how it has evolved from AI, ChatGPT, AI Agent to today. In addition, this chapter describes the benefits of Agentic AI robo-advisory systems for users and financial institutions. Finally, this chapter points out the gaps in research and explains the significance of this study.

1.1 Research Background

1.1.1 What is AI & its evolution

Artificial Intelligence (AI) is a technology that enables machines to exhibit human abilities such as learning, understanding, problem-solving, decision-making, creativity, and autonomy. It can be understood that AI-powered applications can recognize objects, process natural language, learn from experience, and make independent decisions, such as self-driving cars (Stryker & Kavlakoglu, 2024). Meanwhile, ChatGPT is a form of generative AI created by OpenAI and launched in November 2022. It uses deep learning technique, called transformer neural networks to generate human-like text. The transformer can generate coherent, relevant responses (Hetler, 2025). Notably, ChatGPT has become an indispensable part of modern life, helping people save time, improve productivity, and enhance their learning, creativity, and problem solving in work, study, communication, and more. Nevertheless, the new trend and future technology is agentic AI.

1.1.2 AI Agent in financial services industry

In today's rapidly evolving landscape, the integration of AI in the financial services industry has significantly transformed the ways of consumers interact with investment and advisory platforms. Among these innovations, AI-powered robo-advisory systems have gained attention for providing automated financial advice and investment management using AI agents. These robo-advisors provide personalized investment suggestions, manage assets, and improve user experience by leveraging sophisticated algorithms to analyze a large amount of data. This technology makes investment services more accessible, allowing more people to take part in wealth building through tailored advice, risk evaluation, and automated trading strategies (Kaur, 2024).

1.1.3 What is Agentic AI

Agentic AI represents a new stage in analytics, moves from reactive systems to proactive and autonomous intelligence. Traditional AI mainly supports human-led decision-making, but Agentic AI can carry out analytical tasks on its own with little human involvement. These systems use adaptive self-learning algorithms to process structured and unstructured data across different business domains with high accuracy (Parab, 2024). Agentic AI also shows advanced natural language understanding, context awareness, and multi-step reasoning, enabling them to identify complex patterns, correlations, and causal relationships (Parab, 2024). Agentic AI is important especially in finance industry because real-time decision-making and predictive analysis are critical.

1.1.4 Difference between Generative AI and Agentic AI

Generative AI focuses on generate content such as text, images, and audio, driven by statistical pattern recognition (Kshetri, 2024). In financial institutions, Generative AI helps improve

productivity by automating tasks like writing investment reports, handling customer service, and supporting advisory work. For example, Demyttenaere (2023) states that Generative AI helps finance and accounting tasks, especially for one-time analysis and documents. However, Generative AI remains reactive in nature, as it produces output only after receiving user prompts or questions, rather than operating autonomously (Ferraro et al., 2024). Agentic AI, on the other hand, is proactive, autonomous, and works toward specific goals. It continuously monitors financial environments, analyzes real-time data, and makes decisions with little human input. Generative AI mainly supports with communication and reporting, but Agentic AI directly drives decisions and operations, enabling financial institutions to respond faster to changes and risks (Parab, 2024).

1.1.5 Benefits and Competitive Advantage of Agentic AI

The adoption of Agentic AI brings significant advantages to financial institutions. One key benefit is better fraud detection and risk management because autonomous agents can analyze large amounts of data in real time and detect unusual activity early. Agentic AI also improves algorithmic trading optimization, adjust strategies automatically to maximize returns while minimizing risks (Patil, 2025). In addition, Agentic AI supports personalized financial services. It provides tailored investment advice, product suggestions, and financial planning that match individual customer needs, thereby improves customer satisfaction and long-term relationships (Ganesan, 2024). For financial institutions, agentic AI can automate complex tasks such as investment management, fraud detection, and customer support, further improving efficiency, accuracy, and scalability (Ethirajulu, 2023). These capabilities enable financial institutions to provide predictive, customized, and cost-effective financial solutions, improving customer retention and loyalty.

From the users' perspective, Agentic AI robo-advisors are more convenient and accessible than traditional advisors. Users can access Agentic AI robo-advisors 24/7 and gain data-driven insights anytime, anywhere (Ansari & Bansal, 2024). Human investors may be influenced by emotions like fear, greed, or impulsivity when making decisions, but Agentic AI relies on

mathematical models to assess portfolios objectively. This reduces irrational behavior such as panic selling or chasing trends, or holding underperforming assets, thereby supports a more resilient and robust long-term investment strategies (Duodu, 2025). Overall, Agentic AI combines efficiency, accuracy, personalization, and emotionally neutral, provide a clear strategic advantages for institutions, enabling them to outperform traditional financial advisory services in the digital economy.

1.1.6 Why so urgency to study this

The urgency to study Agentic AI stems from its strong potential to reshape the entire financial services industry. Financial institutions are under pressure to adopt advanced AI to remain competitive in the market and meet customer' demands for speed, accuracy, and personalization (Bhatnagar & Mahant, 2024). The global AI finance market is expected to grow from USD 7.3 billion in 2021 to USD 22.6 billion by 2026, thus increasing opportunities for efficiency, cost savings, and customer service improvement (Bhatnagar & Mahant, 2024).

However, rapid adoption also brought challenges because user acceptance of agentic AI robo-advisors remains unclear (Zhu et al., 2024). This situation suggests that innovation is growing, but trust and acceptance may not grow at the same pace. Therefore, it is crucial to understand how users develop trust and acceptance of Agentic AI before these systems are widely used.

For example, Ria, an ASNB robo-advisor, received several negative user reviews that may affect acceptance. One of the issues users reported were poor diversification, with portfolios being overly concentrated on certain assets. Multi-layered of hidden fees reduced transparency in returns, further reduced users trust. Most importantly, its performance was lower than traditional alternatives, such as Amanah Saham Bumiputera (ASB) that offers low-risk fixed-price units (Muzakkir Diah, 2024). These issues show that although robo-advisors are seen as innovative and low-cost, Malaysian investors may not trust or accept them when its

performance and transparency do not meet their expectations. Therefore, it is urgent to understanding how user develop trust and acceptance of Agentic AI robo-advisors.

1.1.7 Why the financial institution is going to look into the Agentic AI

Financial institutions are increasingly adopting Agentic AI because it provides strategic value, operational efficiency, and risk management benefits. It enables real-time fraud detection, predictive analysis for credit and market risks, and automated compliance monitoring, reduced operational risks and better management of regulatory requirements (Patil, 2025).

In addition, Agentic AI ability to process large amounts of financial data allows institutions to generate insights faster than human analysts, which supports more data-driven decision-making (Parab, 2024). At the same time, Agentic AI-driven automation robo-advisory reduces costs, improves accuracy, enhances customer satisfaction, ultimately strengthens competitiveness in an increasingly digital financial environment.

1.2 Problem Statement

Agentic AI is a new direction in artificial intelligence. It refers to an autonomous systems capable of independently pursuing complex goals. Traditional AI depends heavily on structured instructions and strict oversight, but Agentic AI shows adaptability, autonomous decision-making, and the ability to operate effectively in changing environments with little human input (Acharya et al., 2025).

The hedonic, heuristic, utilitarian, and systematic processes describe different aspects of user experience and decision-making. These four facets are important factors that influence user

trust, this trust then leads to the acceptance of Agentic AI robo-advisory systems. In particular, both affective trust and cognitive trust influence how users behave toward AI-driven financial advisory services (Zhao et al., 2025). However, there is still limited research that examines how these four facets affect affective and cognitive trust toward Agentic AI robo-advisors and user acceptance.

Robo-advisors are designed to match portfolios with investors' risk profiles, but there is still lack of studies on how risk tolerance influences user acceptance. Studies shows that investors with higher risk tolerance are more likely to adopt robo-advisors because they perceive automation as a way to accesse diversified portfolios and innovative financial strategies. For example, Fan and Chatterjee (2020) analysed investors in United States (U.S.) and found that those with higher risk tolerance and financial knowledge were more willing to use robo-advisors. Similarly, Hasanudin (2025) examined retail investors in Indonesia and found that matching robo-advisory recommendations with risk tolerance improves portfolio outcomes but does not fully explain the acceptance. A broader study by Manaf et al. (2023) focused on Malaysian youth, highlighted that although risk tolerance is formed in robo-advisors portfolio algorithms, adoption is still limited due to trust issues, lack of human interaction, and low awareness.

In addition, there is also a lack of studies, particularly on Gen Z investors. A research gap emerges on Gen Z investors in Malaysia. This group of investor is highly digitally literate and more willing to try fintech platforms, but they are also more sensitive to trust issues in financial services. Therefore, this study examines how agentic AI attributes in hedonic, heuristic, utilitarian, and systematic processes, together with user segmentation based on risk tolerance, influence trust and influence the acceptance of agentic AI robo-advisory services.

Recent research by Riley and Dixon (2024) explains that affective trust is considered more on emotional and built through repeated experiences of honesty and benevolent adherence, while cognitive trust is usually influenced by factors such as transparency, reliability, and clarity. At the same time, the effects of specific Agentic AI attributes on hedonic (pleasure driven), heuristic (low effort judgments), utilitarian (function driven), and systematic (rational)

processes still not well studies. This leaves gaps in understanding how factors such as perceived pleasure, anthropomorphic, informational, functional, perceived knowledge, and perceived benefits affect users trust formation (Zhao et al., 2025). The lack of a clear framework between Al functionalities (hedonic, heuristic, utilitarian, and systematic) and trust formation makes it difficult for businesses and developers to design Agentic AI systems that balances ease of use and user confidence. The adoption of Agentic Al remains uncertain, and its potential as a reliable and adaptive robo-advisors will be limited without a refined trust model.

It is worth nothing that financial risk tolerance is an important determinant in financial decision-making process. It helps financial institutions predict investors' willingness to invest in short and long-term investments (Bunyamin & Wahab, 2022). Since risk tolerance shapes the acceptance of robo-advisors, low and high risk tolerance are more likely to influence one's financial behaviour, shaping user acceptance of digital advisory systems. As AI-powered robo-advisory systems become increasingly integrated into financial and decision-making processes, existing research predominantly examines overall trust, often overlooking young people's risk tolerance in shaping their agentic AI user acceptance. Furthermore, its role in shaping users' perceptions of agentic AI robo-advisors has not been thoroughly explored.

In addition, according to a recent study by Sun Life Asia (2025), Gen Z faces the steepest climb in achieving financial security, with only 57% of Gen Z respondents feel financially secure. Gen Z has a lower financial security level than Baby Boomers (69%), Millennials (66%), and Gen X (62%). More than half of Gen Z describe themselves as conservative investors, which reflect caution and limited understanding of how to balance risk and long-term returns. Furthermore, more than a quarter of Gen Z do not seek any financial advice. Compared to other generations, Gen Z is the group that most likely to use AI tools for financial advice. Since Gen Z are digital natives, agentic AI robo-advisors are well suited to them (Yılmaz et al., 2024). This highlights the need to investigate how agentic AI attributes influence affective and cognitive trust, leading to user acceptance, and understand the profile's influence on user acceptance, thereby bridging the behavioural understanding gap in agentic AI acceptance in financial service.

1.3 Research Questions

1. Do Agentic Al robo-advisory facets, i.e. hedonic, heuristic, utilitarian, and systematic processing, shape user trust in robo-advisory systems?
2. What role do affective and cognitive trust play in shaping user acceptance of Agentic Al robo-advisors?
3. What role does risk tolerance play in shaping trust and acceptance toward Agentic AI robo-advisors?

1.4 Research Objectives

- To examine how the four facets of Agentic AI (hedonic, heuristic, utilitarian, and systematic processes) shape trust in robo-advisory systems.
- To explore the interplay between affective and cognitive trust in influencing user acceptance of Al-powered robo-advisors.
- To examine how risk tolerance shapes trust and acceptance of Agentic AI robo-advisors across different user segments.

1.5 Scope of the Study

This study examining how Agentic AI attributes in robo-advisors influence investor trust and acceptance in Malaysia. Specifically, it investigates how hedonic, heuristic, utilitarian, and systematic processing affect the acceptance of Agentic AI in financial advisory contexts. The scope of this study focusses on Gen Z users that born between 1997-2007 who use digital

financial services in Malaysia, as this group is highly digital-savvy but remain underexplored in robo-advisory research. The unit of analysis is the individual user. All respondents must be 18 years old or above to ensure they are legally eligible to make financial decision.

1.6 Significance of the Study

The urgency to study this topic arise from the growing reliance on AI-powered robo-advisory systems and the complex relationship between Agentic AI attributes, trust formation, and users' risk profile. As Agentic AI becomes more advanced, it is crucial to understand how hedonic, heuristic, utilitarian, and systematic processes influence affective and cognitive trust in order to further improve the adoption and user satisfaction of agentic AI. This study applied Heuristic-Systematic Model (HSM), and the theory is extended by adding hedonic and utilitarian processing to better understand behavioral AI and behavioral finance in investment decision-making.

This study distinguished between affective and cognitive trust to expand the theoretical understanding of trust formation in AI-powered robo-advisory systems. It also examined how these trust is shaped through hedonic, heuristic, utilitarian, and systematic user interactions.

Practically, the findings of this study can provide guidelines for fintech developers to design a robo-advisory systems that meet different user needs and preferences. By understanding how different agentic AI attributes and user risk profile influence acceptance, fintech developers can design more intuitive, transparent, and trustworthy robo-advisory systems.

For the government or Bank Negara Malaysia, this study provides insights that help in developing responsible agentic AI and user-protection guidelines for financial services. Ultimately, the study contributes to the broader goal of fostering user-centric innovation in the

rapidly evolving fintech sector. In short, this study aims to provide insights for robo-advisory services development.

1.7 Definition of Terms

Terms	Definition
Agentic AI	AI systems capable of autonomous, goal-driven decision-making, showing initiative and adaptability in performing tasks without direct human input.
Robo-Advisory	AI-powered digital platforms that offer automated financial advice or investment management services with minimal human intervention.
Hedonic Processing	Al attributes that enhance enjoyment and emotional engagement.
Heuristic Processing	AI attributes that using simple rules or cues to make quick and efficient decisions.
Utilitarian Processing	Al attributes that facilitate tasks.
Systematic Processing	Al attributes that support logical reasoning and informed decision-making.
Affective Trust	Emotional-based trust, where users form a subjective connection with the Al robo-advisor.
Cognitive Trust	Rational-based trust that depends on logical evaluation of Al capabilities.
AI Literacy	Ability to correctly recognize, efficiently use, and thoughtfully evaluate AI-related tools and systems while upholding ethical standards.
User Acceptance	Willingness to integrate Al-powered robo-advisory services into financial decision-making.

Risk Tolerance	Interpret the advice, intentions, and actions of Agentic AI differently, resulting in varied levels of trust, resistance, or acceptance.

1.8 Chapter Summary

This chapter introduced the research topic and established the foundation for the study by outlining its background, guiding questions, and objectives. It also defined the scope, explained its significance, clarified key terms, and previewed the thesis's structure.

This chapter introduces the research topic and sets the foundation for the study by explaining the background, research questions, and objectives. It also defines the scope, explained the significance of the study, and clarifies the key terms in this study.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter reviews literature related to the Agentic AI attributes and their influence on user acceptance of robo-advisory services through hedonic, heuristic, utilitarian, and systematic processing. It also explains the mediating roles of affective and cognitive trust based on the Heuristic–Systematic Model (HSM). This chapter begins by introducing Agentic AI and robo-advisory services, followed by an in-depth discussion of the independent variables and dependent variable. Theoretical underpinnings and research gaps are presented to justify the study's conceptual model and hypotheses.

2.1 Agentic AI and Robo-Advisory Context

The development of artificial intelligence (AI) has gone through several key stages. From rule-based and lacked adaptability AI systems before 2000s, to the AI systems in the 2000s that integrate machine learning and enhance data-driven decision-making. In the 2010s, deep learning revolution in AI, convolutional neural networks (CNNs) improved image recognition, and the Transformer model improved natural language processing (NLP) with contextual awareness and multimodal capabilities. In the late 2010s, generative AI emerged, which enabled the creation of content such as text, images, and audio. Today, AI systems demonstrate high degree of autonomy, real-time interaction, and self-learning capabilities in complex environments (Hosseini & Seilani, 2025). In the financial industry, AI has been widely applied, especially in robo-advisory services. By leveraging the capabilities of Agentic AI, robo-advisory systems are able to improve efficiency, personalization, and real-time responsiveness.

Agentic AI represents a major advancement in the field of artificial intelligence. Unlike traditional AI systems that typically operated as a tool under strict supervision and fixed rules, agentic AI can set complex goals in uncertain environments and autonomously manage resources to achieve those goals. Traditional AI systems usually perform well in executing structured tasks, but they often struggle or even fail when faced with tasks that lack a clear end-state or do not involve manipulable parameters (Acharya et al., 2025).

Shavit et al. (2023) defined the degree of agentic as the ability of a system to achieve complex goals in complex environments with limited supervision. This concept of agentic includes goal complexity, environmental complexity, adaptability, and independent execution. These attributes together define what constitutes an Agentic AI systems.

In response to changing market conditions, intelligent algorithms and portfolio optimization models were used by Robo-advisors to help users construct portfolio and adjust asset allocation (Luo et al., 2024). While robo-advisors are efficiency and scalable, user adoption is heavily dependent on user trust. This is because users often unaware of the complexity and opacity of underlying algorithms (de Freitas et al., 2023). Lack of awareness and limited knowledge can reduce both customer satisfaction and adoption intentions (Pathak & Bansal, 2024).

In Malaysia, robo-advisory industry has grown under the Securities Commission Malaysia's licensing framework. Platforms such as StashAway, Wahed Invest, MyTheo, and Ria by Amanah Saham Nasional Berhad (ASNB) provide accessible digital wealth management options (Nguyen et al., 2023). Acceptance of robo-advisors has been growing particularly among younger and digitally literate investors in Malaysia. Studies show that perceived benefits, effort expectancy, and social influence significantly affect adoption intention of Malaysia's user, while perceived risk has less impact (Nguyen et al., 2023).

2.2 Conceptualization of Variables

2.2.1 Perceived Pleasure

Perceived pleasure refers to the positive emotional experience that users gain when interacting with a system. In the context of technology use, it refers to how pleasant or enjoyable the user experiences when using the system (Zhao et al., 2025). When users feel enjoyment, this positive emotion can influence how they evaluate the system. Research has shown that perceived pleasure serves as important cues in evaluation and can influence trust formation. When users feel pleasure during an interaction, this positive effect can lead to stronger emotional trust in the system (Zhao et al., 2025).

2.2.2 Anthropomorphism

Anthropomorphism refers to giving human-like qualities to non-human objects. In AI systems, it means perceiving the system as having human characteristics such as emotions, intentions, or social presence. For example, when users describe an AI as friendly or caring, they are engaging in anthropomorphism. Anthropomorphism is a psychological tendency to treat objects as if they were human. In practice, users may respond to the system socially and emotionally if a system exhibits human-like awareness, such as speaking voice or emotional expressions (Zhao et al., 2025). Studies suggests that by creating a sense of social presence, anthropomorphism can enhance user experience. However, its effect on trust may vary depending on the context.

2.2.3 Functional

Functional refers to a systems capabilities and performance. It describes whether a technology has the features and abilities needed to complete its intended work. In other words, functional

is about what the system can do and how well it does it. For example, an AI tool is considered high functional if it reliably generates accurate results or provide useful functions. Functional is one of the key factors influencing user adoption, it depends on how valuable and capable the system seems (Yu et al., 2025). Study by Yu et al. (2025) suggests that users are more likely to adopt new technology if they perceived high functional (performance). Thus, a system that is perceived to work effectively and reliably will increases user trust.

2.2.4 Informational

Informational refers to the quality and clarity of the data provided by the system. It describes the accurate, complete, relevant, and timely available information that users receive from the system. Users will feel confidence in the system when they received high quality information. According to Nicolaou & McKnight (2006), perceived informational quality affect trust directly. For example, when users believe the information provided are reliable and relevant, they feel more confident in the system. In addition, empirical research found that perceived information quality not only increase user trust but also lower their perceived risk (Nicolaou & McKnight, 2006). Therefore, it is critical to ensure that a system provides accurate and comprehensive information in order to build user trust.

2.2.5 Perceived Knowledge

Perceived knowledge refers to how much the users believe they understand or familiar with the technology. It reflects users' confidence in knowing the technology and its capabilities. Users are more able to judge the system's actions when they feel knowledgeable. Higher perceived knowledge means the user believes they know enough to evaluate the system's actions. Research indicates that users perceived knowledge of a technology's capabilities directly affect their cognitive trust in it (Zhao et al., 2025). In short, users are able to make better reasoned

judgments about the system's reliability when they feel informed and knowledgeable, thereby strengthening their cognitive trust.

2.2.6 Perceived Benefit

Perceived benefit refers to the positive outcomes or advantages users perceive from using the system. It is defined as the extent to which users perceive technology as useful and provide tangible advantages for achieving their goals. In other words, perceived benefits are the usefulness users expect from the system. For instance, if a user believes that an AI assistant can save them time or improve decision quality, these are perceived benefits. Research have shown that when users feel the benefits from a technology, they tend to form positive attitudes and trust in it. Specifically, Zhao et al. (2025) defined perceived benefits as the advantages that users expect from the AI. Users trust and willingness to rely on AI increase when they believe the AI is useful and helpful. Thus, highlighting benefits of AI can enhance users' willingness to rely on and trust it.

2.3 Trust in Agentic AI

Trust is crucial when it comes to adopting AI-driven technologies, especially in financial services sector, such as AI-powered robo-advisory systems, where money decisions are involved. Trust is often divided into two dimensions, which is affective trust and cognitive trust. These two dimensions together explain how users form reliance on AI systems beyond technical performance. Recent research by Choung et al. (2023) found that both affective and cognitive trust significantly influence user acceptance of AI agents.

2.3.1 Affective Trust

Affective trust is based on emotions and feeling that develops through empathy, care, and good intentions (Soft Skills Pills, 2025). According to Riley and Dixon (2024), affective trust in AI is often viewed as irrational and built through repeated positive behavior, making users feel more emotionally aligned with the AI system.

Affective trust is defined as the confidence a user places in a partner or system based on feelings that come from the system showing care and concern. Affective trust comes from emotional bonds and a feeling of safety in the relationship. For example, when users feel that a technology cares about them or gives emotional support, they develop affective trust (Johnson & Grayson, 2005; Hsu, 2022). This form of trust is characterised by feelings of security and a sense of emotional connection, rather than by rational analysis.

2.3.2 Cognitive Trust

Cognitive trust is based on logic and reason thinking. It comes from the belief that others have the skills and ability to perform well, and it is often supported by evidence such as past performance or proven results (Soft Skills Pills, 2025). For Agentic AI robo-advisors, cognitive trust reflects how users evaluate technical accuracy, data handling, and decision-making logic.

Cognitive trust is defined as a user's confidence or willingness to rely on another party's ability, reliability, and integrity. This type of trust develops from the evidence and logical thinking about the system's performance. For example, when users believe an AI system is capable and performs consistently, they develop cognitive trust (Johnson & Grayson, 2005; Hsu, 2022). Cognitive trust is built on knowledge and facts that help users predict how a system will behave. It is often described as calculative or ability-based trust, which reflects the expectation that the system will perform as promised.

2.4 User Acceptance of Agentic AI Robo-Advisory

User acceptance of Agentic AI robo-advisors is critical to success in the financial industry. Acceptance refers to users' willingness to adopt and use these systems in their when making financial decisions. Recent advances in fintech have changed investment decision-making toward AI-powered robo-advisory platforms. These platforms match individual preferences and risk profiles by provide automated and low-cost portfolio management (Investopedia, 2025). Thus, understanding user acceptance of AI technologies are crucial to assessing how different users interact with agentic AI robo-advisory systems.

Traditional theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTUAT) are mostly used by previous research to examine user acceptance of new technologies. TAM framework suggests that perceived usefulness and perceived ease of use can predict users' intention to adopt a technology (Davis, 1987). The UTAUT model extends TAM framework by adding factors such as social influence and facilitating conditions.

Singh and Kumar (2024) applied an extended TAM framework and found that trust and perceived usefulness strongly influence users' intentions to adopt robo-advisory services. On the other hand, perceived ease of use had a smaller effect. Sabir et al. (2023) found that perceived ease of use, usefulness, and convenience shaped positive user attitudes toward robo-advisors. This effect depended on users' technology readiness.

A study among Malaysian B40 consumers found that advisory transparency is key in promoting user acceptance of robo-advisors. This study analysed a risk-averse user group with low financial literacy based on the UTAUT framework and found that clear explanations of how

robo-advisors work, along with high performance expectancy and ease of use can increase user acceptance of robo-advisors (Nazmi, Lye, & Tay, 2024).

2.5 Theoretical Frameworks - Heuristic–Systematic Model (HSM)

The Heuristic–Systematic Model (HSM) is a dual-process theory of information processing. It explains how people form judgments through heuristics and systematic processing. Moskowitz et al. (1995) describe HSM as a dual-process theory with two main modes:

Heuristic processing refers to a simple, top-down approach that relies on rules of thumb, schemas, and prior knowledge to understand information quickly. It requires little cognitive capacity and uses cues such as source credibility, consensus, and message length. It is the default mode because it takes the least effort, but it operates only when relevant heuristic cues are present.

Systematic processing refers to a detailed, bottom-up approach that involve careful evaluation of all. It examines arguments closely by integrating new information with existing knowledge. It requires both motivation and cognitive capacity.

In the context of AI, Heuristic–Systematic Model (HSM) helps analysing how users evaluate trust cues (interface design, anthropomorphism), as well as analytical assessments (accuracy, transparency). Several studies applied HSM to examine user–AI interaction. According to Shi et al. (2021), HSM is effective in various areas such as AI Recommendation Systems for travel planning, AI agents (Zhao et al., 2025), and virtual influencers in advertising (Zhu et al., 2024). These studies assessed the contribution of heuristic and systematic processing to AI evaluation, which in turn helps predict user acceptance.

2.5.1 Related theories and their limitation in this context

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) provide valuable insights into factors that affect user acceptance of robo-advisory systems. However, these theories mainly focus on functional and social drivers, omitting affective and cognitive processing pathways that are crucial for building trust in AI decision-making.

Compared to TAM and UTAUT that emphasize general acceptance factors, HSM is better at capturing the dual nature of trust (affective and cognitive) in financial decision-making. For example, some investors rely on heuristic cues, such as the anthropomorphic design of robo-advisor to build trust (affective), while other investors may engage in systematic evaluation of portfolio performance, transparency, and benefits to build trust (cognitive). Recent studies by Vuori, Burkhard, & Pitkäranta (2025) highlighted that dual-path (affective and cognitive) processing significantly influence user acceptance beyond the traditional TAM model.

Therefore, the HSM is chosen as the framework for this study. It addresses both emotional and rational dimensions of trust, which TAM and UTAUT alone do not fully cover. It helps explain how users accept agentic AI robo-advisors by combining feelings of reassurance and judgments of competence.

2.5.2 Dual-Processing Theory: Hedonic and Utilitarian processing

Dual Processing Theory explains how people make decisions using two different processing systems: an intuitive, emotion-based process and a reflective, rational process. In agentic AI robo-advisors, hedonic processing is linked to emotional and pleasure-driven responses, while utilitarian processing focuses functionality, efficiency, and goal achievement. These dual processing explain how users evaluate AI tools beyond mere technical capabilities.

Research suggests that hedonic and utilitarian factors jointly shape user decisions in technology adoption. Schneider (2016) proposed a Dual Process Utility Theory, where decision-making involve affective valuation (hedonic) and rational evaluation (utilitarian), especially under risk and uncertainty. Bellini-Leite (2022) highlighted that Type 1 processes rely on embodied and intuitive judgments, while Type 2 processes rely on structured and symbolic cognition, showing the dual nature of hedonic and utilitarian evaluation.

Hedonic processing is about evaluating pleasure and displeasure. It motivates behavior and affects decision-making (Ellingsen & Leknes, 2015). In AI-powered robo-advisory systems, Zhao et al. (2025) suggest that anthropomorphic characteristic of AI agents can create positive emotional experiences. It strengthens users' affective trust when they rely on AI agents for decision-making and task execution.

Utilitarian processing focuses the right action as the one that maximises overall good, treating the interests of all affected parties equally. In business, it aims to maximising benefits and minimizing harm. In AI-powered robo-advisory systems, utilitarian value comes from functionality and informational quality, including AI's ability to enhance efficiency, improve accuracy, and provide relevant, reliable, and well-structured financial insights. These utilitarian benefits strengthen cognitive trust, as cognitive trust is form based on users' rational evaluation and logical reasoning (Zhao et al., 2025).

Dual Processing Theory explains how hedonic and utilitarian evaluations influence the adoption of Agentic AI. While hedonic processing emphasizes emotional satisfaction and user enjoyment, utilitarian processing emphasizes functional reliability and problem-solving capabilities. These dimensions together explain how users build trust and acceptance of agentic AI robo-advisors.

2.5.3 Analytical and cognitive evaluation: Systematic Processing

Systematic processing involves careful and effortful analysis of information. It required deep thinking and intensive reasoning, leading to higher confidence in judgmental (Chaiken & Ledgerwood, 2012). In AI-powered robo-advisory systems, users' knowledge and perceived advantages of these systems influence cognitive trust.

The Heuristic–Systematic Model (HSM) highlights that systematic processing involves intensive reasoning, close attention, and critical evaluation when users are motivated and able to think deeply (Chaiken & Ledgerwood, 2012). In AI context, this related to accessing the transparency and functional reliability of AI. Research on high-level thinking shown that analytical processing enhances users' confidence in AI-assisted decision-making by helping them to compare AI advice with their personal knowledge (Ragni, 2020).

According to Zhao et al. (2025), it is found that higher perceived knowledge of AI-powered robo-advisors strengthens users' cognitive trust, as it leads them to make more rational evaluations. When users perceive clear benefits, they are more likely to develop stronger cognitive trust, thereby enhancing their acceptance and willingness to use AI agents.

However, cognitive limits may reduce systematic evaluation. Users often rely on heuristic cues (low effort judgement) such as interface design or perceived credibility when they lack time or motivation. Thus, systematic processing does not always occur, even in making important decisions (Chaiken & Ledgerwood, 2012).

Systematic processing provides a theoretical foundation for understanding how users cognitively engage with AI systems, emphasizing analytical trust-building. However, its effectiveness depends on the specific context, and is often moderated by users' cognitive ability, motivation, and AI literacy.

2.6 Hypothesis Development

2.6.1 The relationship between Affective Trust and User Acceptance

Affective trust is an emotional bond that involves feeling of safety, understanding, and connection. Especially in financial contexts with high risk and uncertainty, affective trust has been demonstrated to positively influences users' willingness to adopt AI agents, (Zhao et al., 2025).

Many studies show that affective trust enhances user acceptance of AI-driven financial technologies. Hildebrand and Bergner (2021) found that conversational robo-advisors create higher affective trust than static systems. This leads to higher acceptance of recommendations and investment decisions. This occurs because human-like interaction provides social cues and a sense of being heard or understood, which strengthens emotional connection. Singh and Kumar's (2024), based on of 454 responses, confirmed that trust with an emotional element of vulnerability and expectation has a strong and positive effect on users' attitudes toward robo-advisors adoption. Shang et al. (2024) developed a scale to measure affective and cognitive trust in AI agents. Their findings shown that affective trust plays an important role in AI acceptance because it creates emotional connection beyond logical evaluation. This is because affective trust reflects feelings such as goodwill and care, which help reduce trust gaps in AI systems. Bernardo and Seva (2023) highlighted that emotional responses such as happiness, fear, and suspicion directly affect trust in explainable AI (XAI). Positive emotions such as surprise or trust enhance affective trust and reliance on AI recommendations. On the other hand, negative emotions such as fear, anxiety, or doubt do not significantly affect trust (Bernardo and Seva, 2023). When users feel that the AI understands them or communicates in a calm and personal way in agentic AI robo-advisory system, they may develop affective trust. Pathak and Bansal (2024) found that affective trust helps build relationships and reduce emotional distance between users and non-human agents. In the banking, financial services, and insurance (BFSI) sector, emotional experiences of care, reliability, and safety creating positive feelings and a sense of closeness that significantly encourages adoption (Pathak and Bansal, 2024).

Some studies argue that affective trust impact may be weaker or not significant in highly rational domains like finance. Luo et al. (2024) reported that investors often follow the advice of robo-advisors with low anthropomorphic features when investment are complex. Bernardo and Seva (2023) found that negative emotions reduce satisfaction and reliance even when explanations are provided. This suggest that affective trust alone may not support long-term acceptance and works best together with cognitive trust.

Users' perceived pleasure and anthropomorphism will increase affective trust, thereby enhancing users' acceptance of agentic AI robo-advisors. Evidence consistently supports that affective trust is a positive driver of AI adoption, although some researchers argue that its effectiveness may be limited without rational assurances. This highlights the need to examine how different processing routes (hedonic, heuristic, utilitarian, systematic) shape the way agentic attributes influence trust in agentic AI robo-advisory systems.

H1. The users' affective trust of Agentic AI robo-advisors positively influences user acceptance.

2.6.2 The relationship between Cognitive Trust and User Acceptance

Cognitive trust is based on rational judgement of competence, reliability, and transparency. In Agentic AI robo-advisors, cognitive trust reflects users' belief that the system can provide accurate and unbiased investment recommendations. Cognitive trust comes from belief in the AI's capabilities and reliability can significantly increases user acceptance of AI systems (Zhao et al., 2025).

Research suggests that cognitive trust strongly predicts user acceptance of robo-advisors. Pathak and Bansal (2024) found that cognitive trust is a key factor in investors' adoption of

AI-powered robo-advisors. Their study shown that perceived benefits and functionality drive usage intention. When users perceived the AI as accurate, reliable, and capable, cognitive trust grows, making them more willing to rely on the system in financial decision-making. Experimental findings shown that users follow investment recommendations more often when they perceive the robo-advisor as competent and reliable. Users develop higher acceptance and reliance due to higher perceived competence and reliability reduce users' mental effort and stress (Panchetti et al., 2023). Bernardo and Seva (2023) highlighted that explainable AI (XAI) improves cognitive trust by showing users how decisions are made. Clear explanations enable users to understand the system and judge its logic, helps them adjust their level of trust based on evidence. According to Riley and Dixon (2024), cognitive trust in AI depends on tangibility, transparency, and reliability. These factors support users' rational judgments of the AI's competence and consistency. A cross-domain AI study shows that trust has both affective and cognitive components. Cognitive trust, based on perceptions of performance and accuracy, often has a stronger influence on acceptance than affective trust (Choung et al., 2023). Cognitive trust comes from reliable task execution, technical strength, and accurate results. It directly addresses users' rational concerns about effectiveness. Cognitive trust forms when users perceive AI decisions to be accurate, transparent, and consistent in financial services.

In general, systematic processing enhances cognitive trust because users evaluate AI rationally. Still, some studies warn about over trust. Schütz et al. (2023) demonstrated that ability and integrity in robo-advisors increased cognitive trust. However, they also found that systematic evaluations can still overlook critical human-like attributes, as a lack of benevolence reduces the reliability of such cognitive trust. Nagadeepa et al. (2023) also argued that poor transparency and low personalisation reduce cognitive trust, even when robo-advisors provide rational and data-driven decisions. Cognitive trust in fairness and reliability declines when users do not understand the decision process or feel ignored. Fatima and Madhumita (2024) found that anxiety and preference for human advisors weaken the effect of cognitive trust on adoption. The high-risk nature in financial decisions increases emotional discomfort, causing users to rely more on human empathy and accountability than on system capabilities. Shang et al. (2024) noted that cognitive trust alone may not be sustainable in long-term, an emotional connection is often the basis for continued acceptance. Affective trust supports cognitive trust by adding warmth and empathy in relationships, especially in advanced human-like AI agents.

Cognitive trust provides rational foundation for user acceptance by ensuring users perceive agentic AI robo-advisors as competent and reliable. Although adoption is strongly predicted by cognitive trust, risks can arise when the system is relied on too much without critical oversight.

H2. The users' cognitive trust of Agentic AI robo-advisors positively influences user acceptance.

2.6.3 The relationship between Perceived Pleasure and Affective Trust

Perceived pleasure refers to the enjoyment and satisfaction users feel when they interact with AI systems. Enjoyment from AI interactions, such as an engaging interface or a warm tone, has been found to significantly enhance affective trust (Zhao et al., 2025). Perceived pleasure is closely linked to affective trust because enjoyable interactions strengthen emotional bonds and create a sense of comfort with AI technology.

Studies show that perceived pleasure plays an important role in building affective trust in AI systems. Ding and Najaf (2024) reported that perceived pleasure affects AI chatbot adoption. Perceived enjoyment enhances the positive emotional experience during interactions with chatbots. This makes users feel more satisfied, thereby increases affective trust and raises willingness to adopt chatbots for e-commerce (Ding and Najaf, 2024). When using AI feels fun, engaging, or emotionally satisfying, users form positive feelings toward the system. Rouibah et al. (2016) found that enjoyment in an online payment platform strongly drive affective trust and adoption. Perceived enjoyment creates a pleasurable and fun experience. This experience builds emotion-based (affective) trust and directly increases intention to use the service, even when users perceived risk in the service. Recent research by Huang et al. (2024) confirmed that perceived enjoyment significantly predicted enjoyment and future use of AI services in hospitality context. Customers gain hedonic value that fulfils their expectations when they find AI interactions are fun and emotionally rewarding. This leads to higher satisfaction and a stronger intention to continue using AI services.

However, some studies show that the relationship between perceived pleasure and affective trust depends on context. Zhang and Yang (2022) found that human-like designs in service robots did not always increase anthropomorphism or affective trust. In some cases, robots with human-like features were seen as less intelligent than machine-like designs. This happens when users expect human-level ability have not been met and feel disappointed. At the same time, interaction features alone failed to significantly improve these views. It can cause discomfort or suspicion rather than emotional connection and affective trust if the robot's design is overly human-like (Zhang and Yang, 2022).

Perceived pleasure increases affective trust in Agentic AI robo-advisors by creating enjoyable and emotionally engaging experiences. The strength of this relationship is influenced by design and interaction quality, which highlights the need for context-sensitive implementation.

H3. The users perceived pleasure of Agentic AI robo-advisors positively influences affective trust.

2.6.4 The relationship between Anthropomorphism and Affective Trust

Anthropomorphism refers to the perception of human-like features, personalities, or behaviours on AI systems. Anthropomorphic design enhances emotional engagement, makes users more likely to develop affective trust in agentic AI robo-advisors. Anthropomorphic elements strengthening users' affective trust in robo-advisory systems by giving AI human-like traits that activate social schemas and enhance emotional bonding (Plotkina et al., 2024). Anthropomorphism helps reduce the psychological distance between humans and AI by expressing empathy, social presence, and familiarity.

Research supports the relationship between anthropomorphism and affective trust. Chi and Vu (2022) found that anthropomorphism enhances user emotional (affective) trust when combined with empathy responses and interactive communication quality, highlighting its emotional influence on affective trust formation. Chi and Vu (2022) explain that anthropomorphism fosters friendliness and affective relationships by making AI seem more human-like, thereby enhancing social attraction and acceptance; however, it builds trust only indirectly through improved communication quality, whereas empathy directly contributes to emotional assurance in various service contexts. Polyportis and Pahos (2024) highlighted that anthropomorphism positively influences students' attitudes and adoption of ChatGPT by attributing human-like characteristics, attributing human-like feelings, mental states, increasing perceived social presence and relatability, making students more likely to form favourable attitudes as it mimics natural human interactions and fosters a sense of connection essential for technology acceptance.

However, the effect of anthropomorphism is not always straightforward. Inie et al. (2024) found that anthropomorphized descriptions of AI systems did not universally increase emotional (affective) trust; instead, the type of product and context determined whether anthropomorphism strengthened or weakened emotional (affective) trust, because anthropomorphism is an aggregate concept comprising different categories (cognizer properties, agency, biological metaphors, and communicator properties) that interact variably with specific system types and use contexts, leading to nuanced rather than uniform effects on trust without a simple binary relationship. While anthropomorphic appearance influenced perceptions of bias, its effect on affective trust was moderated by the richness of AI explanations (Hou et al., 2024). Higher human-likeness in a biased AI can increase users' emotional reactions to perceived unfairness. Over-reliance or excessive emotional attachment can be reduced by clear explanations by improving transparency and allow users to check the system's decisions carefully.

Anthropomorphism enhances affective trust in Agentic AI robo-advisors by creating emotional bonds and social attraction. However, its influence depends on context and design features such as empathy, communication quality, and explanation richness.

H4. The anthropomorphism of Agentic AI robo-advisors positively influences affective trust.

2.6.5 The relationship between Functional and Cognitive Trust

Functional refers to the system's ability to perform reliably, deliver accurate recommendations, and meet user expectations in task execution. The functionality of an AI system, how useful, clear, and effective it is perceived to be, has been shown to strengthen cognitive trust by bolstering users' rational confidence in its operations (Lee et al., 2023). In Agentic AI robo-advisors, functionality is directly linked to cognitive trust, as users form rational judgments about whether the system is competent and dependable.

Maier et al. (2022) showed that in financial AI, performance differences between human and AI advisors moderately influenced cognitive trust, with higher-performing AI systems fostering greater cognitive trust because in domains where humans and AI exhibit similar baseline capabilities, evaluating the AI's performance relative to the user's own performance reveals the incremental value provided by the AI, user perceived AI as more functional, resulting in increased cognitive trust. Vanneste and Puranam (2024) found that cognitive trust in AI systems is supported by functional and perceived ability. Users trust AI more when it works reliably. When AI is given intentionality and goal-directed actions, users evaluate its competence and reliability better. Its ability to do tasks well can be evaluated by users without relying on emotional or experiential cues.

While cognitive trust can be enhanced by functional factors, scholars warn that over-trust may pose risk. Henrique and Santos (2024) highlighted that automation can be misused and leading to negative outcomes if AI recommendations are followed without critical evaluation. Users' expectations must be balanced with AI capabilities. Confidence is built by functional features, but blind reliance must not be encouraged.

Cognitive trust in agentic AI robo-advisors is positively shaped by functional features that demonstrate reliability and competence. Transparency and oversight must complement functional features to prevent over-trust.

H5. The functional of Agentic AI robo-advisors positively influences cognitive trust.

2.6.6 The relationship between Informational and Cognitive Trust

Information quality is a key factor in building cognitive trust in AI systems. In agentic AI robo-advisors, high-quality information means investment advice that is accurate, timely, relevant, and easy to understand. Users use this information to rationally evaluate the competence and reliability of the AI system, so cognitive trust is formed. Clear information and transparency about how the AI works help users build understanding and increase cognitive trust (Lee et al., 2023).

Belanche et al. (2019) showed that the adoption of robo-advisors depends on how reliable users perceive the information to be, and accurate financial advice is the main driver of cognitive trust. Information that is complete, accurate, timely available, and relevant shapes users' belief that the robo-advisor can improve financial performance through efficient and accurate advice. This belief increases cognitive trust and adoption intention. Another research shown that reliable information helps users build rational confidence in robo-advisors. Research pointed out that reducing human bias and improving transparency are important for building investor cognitive trust. Robo-advisors use objective algorithms instead of subjective human judgment, thereby they can provide clear and data-driven advice. This improves accessibility, reliability, and lowers cost in financial advisory services (Nagadeepa et al., 2023).

Even though information quality usually strengthens cognitive trust, weak or distorted information can reduce user confidence. Schütz et al. (2023) found that reliability and integrity

increase cognitive trust in robo-advisors, but missing elements like benevolence reduce users' acceptance of investment advice. Benevolence means that users believe the advisor acts in their best interest without selfish motives. This quality is hard to show in automated systems that lack human interaction and social signals, so cognitive trust may not be form. Nagadeepa et al. (2023) also stated that low-quality or biased information threatens investor trust and limits adoption even when the system works well. Robo-advisors are designed to solve problems found in human advisory by using objective and algorithm-based advice. However, if users perceive the information as flawed or biased, they lose confidence in the system's reliability and objectivity, which reduces their willingness to use it.

Cognitive trust in agentic AI robo-advisors is positively influenced by information quality through improved accuracy and reliability of decision support. Inadequate or misleading information can reduce trust and show the need for clear and high-quality data delivery.

H6. Information of Agentic AI robo-advisors positively influences cognitive trust.

2.6.7 The relationship between Perceived Knowledge and Cognitive Trust

Perceived knowledge refers to a people belief about how well they understand AI systems. In agentic AI robo-advisors, users who feel more knowledgeable can evaluate the system more easily, thus cognitive trust strengthened through rational judgment of its ability and transparency. Users' own understanding of how AI works reduces uncertainty and builds cognitive trust (Zhao et al., 2025).

Recent studies shown that perceived knowledge strengthens cognitive trust in AI systems. Yi et al. (2023) found that millennials with higher financial knowledge showed stronger trust and higher willingness to use robo-advisory services. This happens because knowledge helps them to understand how these tools work and what benefits they provide, which improves their financial decisions. Ashrafi (2023) found that perceived financial knowledge affects the

relationship between perceived value and intention to use AI-powered robo-advisors. When accessing the value of robo-advisors services, users who believe they have higher financial knowledge are more confidence, thereby cognitive trust and adoption intention increase. Luo et al. (2024) reported that education and user knowledge improve investors' views of robo-advisor reliability. Knowledge gives users useful skills that support the advisory process, so perceived value increases and adoption intention grows through stronger cognitive trust.

However, knowledge does not always lead to trust. Li et al. (2025) found that while higher AI knowledge improved comfort and perceived benefits in healthcare contexts, it did not always translate into greater trust, particularly when ethical or reliability concerns were present. Their findings challenge the deficit model by showing that familiarity with AI can also lead to discomfort as people become aware of potential issues such as data privacy risks, job automation, and ethical governance shortcomings that require transparency and robust safeguards to foster cognitive trust. This indicates that while perceived knowledge often enhances trust, contextual concerns may mediate the strength of this relationship. Li et al. (2025) found that higher AI knowledge increased comfort and perceived benefits in healthcare, but it did not always increase trust when ethical or reliability issues existed. Their findings shown that knowing more about AI can also raise concerns about data privacy, job automation, and ethical problems. These concerns can reduce cognitive trust when transparency and safeguards are weak. This shows that perceived knowledge often supports cognitive trust, but the effect may depend on the situation.

Cognitive trust in Agentic AI robo-advisors is positively influenced by perceived knowledge through informed evaluation of system reliability and transparency. However, explainability and fairness must support knowledge to fully build user confidence.

H7. The users perceived knowledge of Agentic AI robo-advisors positively influences cognitive trust.

2.6.8 The relationship between Perceived Benefit and Cognitive Trust

Perceived benefit refers to how users' evaluation the advantages of using AI technologies such as efficiency, low cost, easy access, and better decision-making. These benefits strengthen cognitive trust because users logically assess the system's value of agentic AI robo-advisors in supporting financial decisions. Benefits such as saving time, improving returns, and offering better decision support strongly predict cognitive trust because they directly meet users' utilitarian concerns (Zhao et al., 2025).

Research shows that perceived benefits significantly enhance cognitive trust in robo-advisors. Yi et al. (2023) found that millennials adopted robo-advisory services mainly due to perceived usability and cognitive trust. Benefits like convenience and improved financial knowledge shaped their intention to adopt these services. Users feel that the platform is easy and efficient to use when they perceived high usability. This helps them clearly see the benefits of robo-advisors in providing objective, personalised, and accessible wealth management. Sabir et al. (2023) found that perceived usefulness and convenience positively influenced user attitudes toward robo-advisors and strengthened cognitive trust. Users logically assume that robo-advisors are competent and reliable when users believe it can improve investment results by automated, data-based decisions, and allow access at any time. Luo et al. (2024) further explained that investors' willingness to use robo-advisors depends on performance, ease of use, and customer education. Strong performance, intuitive interfaces, and educational support help users evaluate efficiency, accuracy, and tailored advice. This creates perceived benefits and strengthens cognitive trust.

Different user groups may have different perceived benefits. Ramesh et al. (2023) found that millennials valued access and transparency to information, but less tech-savvy investors remained doubtful. This shows that basic digital literacy and user readiness are important for perceived benefits to translate into cognitive trust. Robo-advisory platforms mainly target tech-savvy millennials and Gen X users investors value full-time access, lower costs, unbiased advice, and transparency from AI systems. In contrast, due to bias and poor understanding of how the technology works, investors with limited knowledge may hesitate.

Cognitive trust in agentic AI robo-advisors is fostered by perceived benefits that highlight efficiency, convenience, and improved decision-making. Although the effect is generally positive, user readiness and technological familiarity affect cognitive trust, meaning that perceived benefits alone may not guarantee cognitive trust without supportive adoption conditions.

H8. The users perceived benefit of Agentic AI robo-advisors positively influences cognitive trust.

2.7 Conceptual Framework Diagram

Figure 2.1 illustrates the proposed conceptual framework. It is based on the Heuristic–Systematic Model (HSM). This model explains that people process information in two main ways, which are heuristic processing and systematic processing.

Hedonic processing is an emotional and pleasure-based response to agentic AI robo-advisors, and it activates the heuristic route. The trust factors in this route is the perceived pleasure. Perceived pleasure refers to the enjoyment users feel when they interact with AI systems, and this enjoyment can increase affective trust. Heuristic processing is a mode of thinking that based on simple decision rules or if-then associations. The trust factors in this route is the anthropomorphism. Anthropomorphism means giving AI human-like features, and this increases user engagement and emotional connection. Research shows that anthropomorphic AI products increase purchase intention and brand evaluation because they raise entertainment value in hedonic settings (Zhang & Wang, 2023). Xie et al. (2023) also found that medium levels of anthropomorphism improve interaction quality, especially in hedonic use, and this strengthens affective trust. Trzebiński (2023) further explained that anthropomorphic cues improve users' responses to hedonic messages and show the AI's learning ability. Hedonic

processing reflects an emotion-driven path where enjoyment and anthropomorphism build affective trust in AI systems.

Utilitarian and systematic processing focus on practical and analytical evaluation of Agentic AI robo-advisors, and they activate the systematic route. These constructs show different ways users understand and react to the AI's agentic features. Utilitarian processing refers to rational and goal-focused evaluation of AI systems, and it focuses on functional and informational value. Functional refers to the AI's ability to provide accurate and reliable services, and information quality refers to how relevant and useful the AI's outputs are. Fernandes et al. (2020) showed that utilitarian AI supports long-term adoption because it aligns with human values and emphasis on functional reliability. From an information processing view, Makkonen (2021) explained that users adopt innovations not only because they are easy to use, but also because the information is sufficient and useful. Users rely on AI when they believe the information has enough quality and value. Utilitarian processing supports cognitive trust because users judge whether the AI provides reliable, useful, and functional support for decision-making.

Systematic processing involves careful and effort-based evaluation of AI systems based on perceived knowledge and perceived benefits. Users with higher AI knowledge are more likely to examine information and assess risks and benefits in detail, so they develop stronger rational trust. Zhu et al. (2016) showed that perceived knowledge predicts information seeking and systematic processing, which supports deeper evaluation. In AI context, Said et al. (2023) found that knowledge and confidence affect how users compare risks and benefits. Higher knowledge increases perceived benefits, but it can also reduce awareness of possible risks. Systematic processing strengthens cognitive trust because users base their decisions on informed, knowledge-based, and benefit-focused evaluation.

The framework identifies two trust outcomes from these processing routes, which are affective trust and cognitive trust. Affective trust is an emotion-based connection, such as feeling safe or comfortable with the AI, and it develops when users rely on heuristic processing after pleasant interactions. Cognitive trust is a reason-based belief in the AI's ability, reliability, and honesty,

and it develops when users carefully evaluate the system and find its logic, performance, or transparency convincing.

The dependent variable is user acceptance. User acceptance refers to the willingness to adopt and rely on the agentic AI robo-advisor for investment decisions.

Figure 2.1: Conceptual Framework

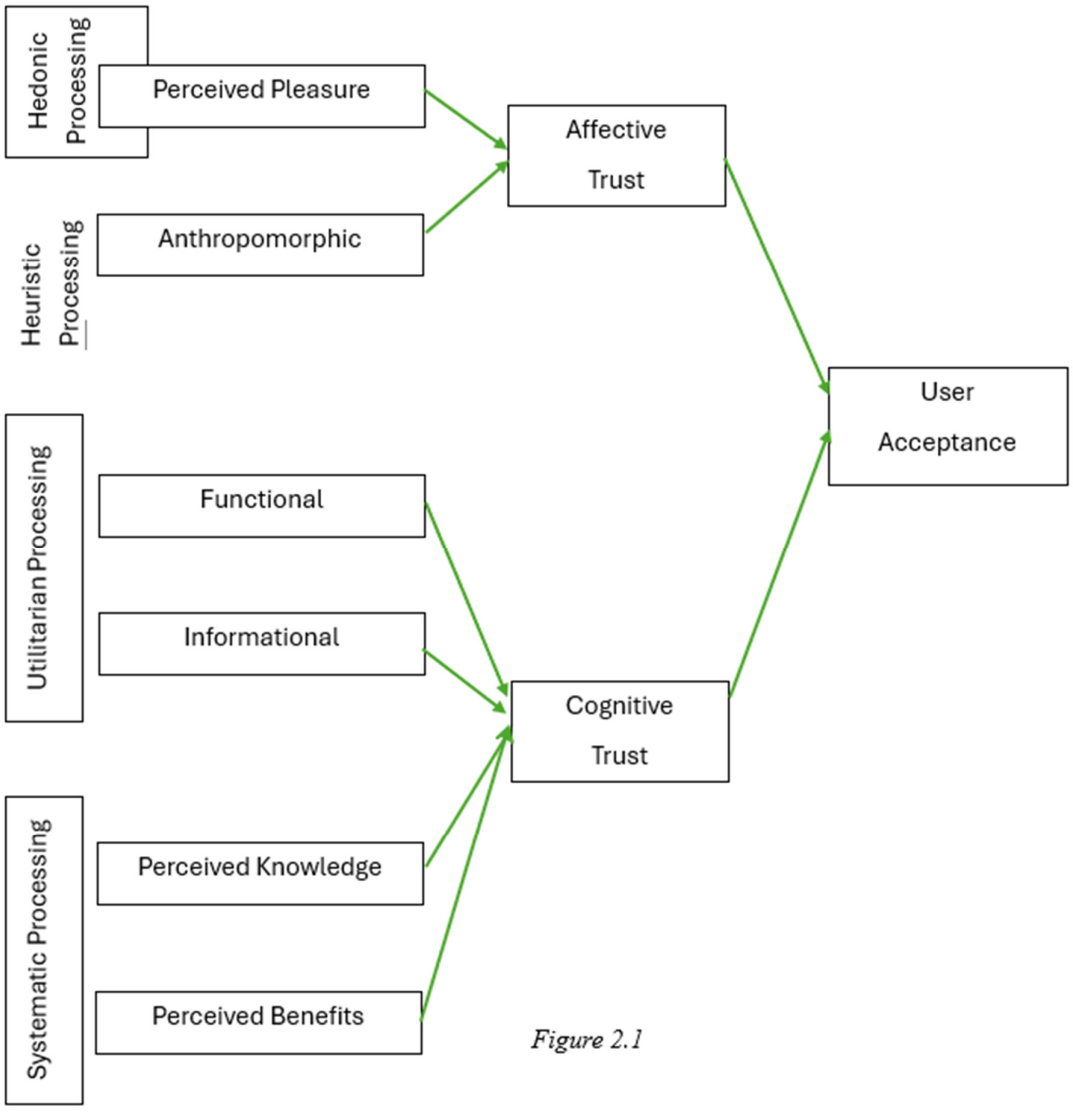


Figure 2.1

Source: Developed for the research

2.8 Summary

This chapter reviewed the theoretical and empirical foundations for the study. It covered agentic AI, robo-advisory services, processing types, trust types, user acceptance, and the Heuristic-Systematic Model (HSM).

CHAPTER 3: Research Methodology

3.0 Introduction

This chapter describes the methodology used to study the effects of hedonic, heuristic, utilitarian, and systematic processing on affective trust, cognitive trust, and user acceptance of agentic AI robo-advisors. The chapter first explains the research philosophy and research design. Following by sampling method, research tools, and measurement scales. The chapter also explains the steps used to reduce common method bias, the pilot test, and the data collection process. The methods used for data processing, testing, and analysis are also explained to ensure validity and reliability when testing the proposed hypotheses.

3.1 Research Philosophy

This study is guided by the positivist philosophy, which assumes that reality is objective, measurable, and can be studied independently of the researcher. Positivism emphasizes the use of observable facts and quantitative data to test theory-driven hypotheses, thereby generating findings that can be generalized (Ryan, 2018).

This study follows a positivist philosophy, which assumes that reality is objective, measurable, and can be studied separately from the researcher. Positivism focuses on observable facts and quantitative data to test theory-based hypotheses. This approach helps produce findings that can be generalized (Ryan, 2018).

Positivism is appropriate for this study because the study examines causal relationships between hedonic, utilitarian, and systematic processing and their effects on affective trust, cognitive trust, and user acceptance of agentic AI robo-advisors. Using structured questionnaires and statistical analysis helps maintain the objectivity of findings and reduces researcher bias.

Based on positivism, this study uses a deductive reasoning approach. The hypotheses (H1–H8) are derived from the literature on the Heuristic–Systematic Model (HSM) and empirical research. This approach allows the study to test theoretical assumptions through hypothesis testing.

3.2 Research Design

This study uses a quantitative research design. It systematically collects and analyses numerical data to identify patterns, test hypotheses, and make general conclusions. Quantitative research is useful for examining relationships between variables. It fits the positivist philosophy, which claim reality exists independently of the observer and can be measured through observation.

By using structured instruments like questionnaire and standardized scales, the research design ensured reliable and replicability results. These tools measure user perceptions, trust, and acceptance of agentic AI robo-advisors (Bhandari, 2020). Furthermore, the results can apply to a wider population by using a large sample sizes (Park, 2020).

3.3 Data Collection

3.3.1 Target Population

The target population for this study is Gen Z individuals (18–28 years old, born 1997–2007) in Malaysia. Gen Z are either current users or potential adopters of robo-advisory services (Sun Life Asia, 2025). Individuals born in 2008 or later are excluded because they are under 18 years old, the legal minimum age for investment, and are unlikely to use financial platforms. This population is appropriate because it represents digitally savvy individuals who are likely to adopt agentic AI financial technologies.

3.3.2 Sampling Frame and Location

The sampling frame includes digitally savvy Gen Z individuals living in Malaysia. The study included respondents from all over Malaysia to ensure diversity and representativeness. This approach reflects the views of Gen Z from different geographic and socioeconomic backgrounds.

3.3.3 Sampling Elements

The sampling elements are individual Gen Z respondents. They meet the age requirement and have experience or interest in using robo-advisory services.

3.3.4 Sampling Techniques

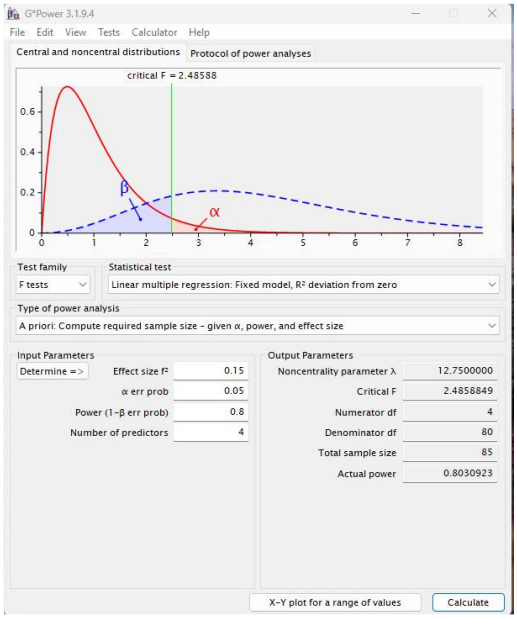
This study uses purposive sampling, a nonprobability sampling technique. Purposive sampling focuses on individuals most likely to provide meaningful insights on the use or adoption of agentic robo-advisory services. This method does not require a randomly selected sample. This is useful especially when the population is not easy to access or well-defined (Etikan et al., 2016).

The technique helps identify participants from different backgrounds, including urban and rural areas. It also considers the differences exposures to digital investment platforms. By focusing on relevance over randomness, purposive sampling ensures the collected data reflects the population segment of interest. This method is efficient for data collection within limited time and resources, making it a practical choice for this study.

3.3.5 Sample Size

The minimum sample size required is determined using G*Power software with a medium effect size ($f^2 = 0.15$), significance level 0.05, and power 0.80. The calculation indicates that at least 85 respondents are required. As suggested by Memon et al. (2020), the target sample size is 160 to 300 respondents to increase reliability and reduce non-response bias. The goal of this study is to collect 350 responses to account for incomplete or unusable data, ensuring enough valid responses for statistical analysis.

Figure 3.1: G*Power Test



Source: Developed for the research

3.4 Instruments and Measurements

3.4.1 Questionnaire Design

The questionnaire was the main tool to collect quantitative data from respondents. It had four sections to ensure clarity and logical flow.

Section 1: Demographics

This section collected background information such as age, gender, education level, income, state of residence, investment experience, prior use of robo-advisors, and AI literacy. These variables helped to analyse the characteristics of respondents and compare subgroups.

Section 2: Risk Tolerance

This section measured respondents' risk tolerance, which is their attitudes toward financial risk using items from an established financial risk assessment frameworks.

Section 3: Constructs

This section measured the study's independent variables (hedonic, utilitarian, and systematic processing), and dependent variable (affective trust, cognitive trust, and user acceptance). Based on prior research on adoption and trust by Joshi et al. (2015), the items were measured using a five-point Likert scale, from 1 = Strongly Disagree to 5 = Strongly Agree.

This structure design ensured ease of completion, minimized respondent fatigue, and aligned with best practices in behavioural and technology adoption studies (Hair et al., 2019).

3.4.2 Instrument Development

Table 3.1: Instrument Development

Construct	Items	Source
Perceived Pleasure	PP1: I think I would enjoy using the Agentic AI robo-advisor. PP2: Interacting with the Agentic AI robo-advisor is likely to feel pleasant. PP3: The Agentic AI robo-advisor would make investing feel more fun and engaging.	Adapted from Zhao et al. (2025)
Anthropomorphism	AN1: The Agentic AI robo-advisor communicates like a human. AN2: The Agentic AI robo-advisor behaves in a human-like way.	Adapted from Zhao et al. (2025)

	AN3: The Agentic AI robo-advisor will experience emotions.	
Functional	FT1: The Agentic AI robo-advisor would help me to generate better investment return. FT2: The Agentic AI robo-advisor offers useful investment tools and features. FT3: The Agentic AI robo-advisor helps me save time by automatically managing my investments and providing instant reports.	Adapted from Zhao et al. (2025)
Informational	IF1: The Agentic AI robo-advisor provides clear explanations for its recommendations. IF2: The Agentic AI robo-advisor gives enough details for me to understand why it made a recommendation. IF3: The information from the Agentic AI robo-advisor is easy to understand.	Adapted from Zhao et al. (2025)
Perceived Knowledge	PK1: I feel I understand how Agentic AI robo-advisors work. PK2: Compared to most people, I know more about Agentic AI robo-advisors. PK3: I am confident in my knowledge of what Agentic AI robo-advisors can and cannot do.	Adapted from Zhao et al. (2025)
Perceived Benefit	PB1: Using the Agentic AI robo-advisor would likely improve my investment returns. PB2: The Agentic AI robo-advisor would provide personalised recommendations that fit my goals.	Adapted from Zhao et al. (2025)

	PB3: The Agentic AI robo-advisor makes daily financial management easier by reducing costs and saving time.	
Affective Trust	AT1: I would feel comfortable letting the Agentic AI robo-advisor handle my investment needs. AT2: I feel the Agentic AI robo-advisor would understand my personal investment preferences. AT3: I feel secure relying on the Agentic AI robo-advisor for important financial decisions.	Adapted from Zhao et al. (2025)
Cognitive Trust	CT1: I believe the Agentic AI robo-advisor is competent in making investment decisions. CT2: I believe the Agentic AI robo-advisor gives reliable and accurate recommendations. CT3: I believe the Agentic AI robo-advisor will act in a consistent and dependable way.	Adapted from Zhao et al. (2025)
User Acceptance	UA1: I intend to try an Agentic AI robo-advisor in the future. UA2: I would recommend an Agentic AI robo-advisor to friends or family. UA3: I am willing to rely on an Agentic AI robo-advisor regularly.	Adapted from Zhao et al. (2025)

Source: Developed for the research

3.5 Measurement Scales

This study employed both categorical and continuous measurement scales to capture demographic, risk tolerance, and construct-related data.

Table 3.2 Scale for Categorical Data

Variable	**Scale**	**Coding**
Gender	Nominal	1 = Male 2 = Female
Age Group	Ordinal	1 = 18–21 2 = 22–24 3 = 25–28
State of Residence	Nominal	1 = Johor … 13 = Sarawak
Education Level	Ordinal	1 = Secondary school 2 = Pre-University/Diploma/Foundation 3 = Bachelor's degree 4 = Master's degree
Monthly Income	Ordinal	1 = < RM2,000 2 = RM2,000–3,999, 3 = RM4,000–5,999 4 = RM6,000–7,999 5 = RM8,000–9,999 6 = RM10,000 and above
Investment Experience	Ordinal	0 = No experience

		1 = < 1 year 2 = 1–3 years 3 = 4–6 years 4 = > 6 years
Prior Use of Robo-Advisors	Nominal	1 = Yes 2 = No
Agentic AI Understanding	Ordinal	1 = None 2 = Basic 3 = Intermediate 4 = Advanced
Perception of AI replacing human advisor	Ordinal	1 = Positive 2 = Neutral 3 = Negative

Source: Developed for the research

Table 3.3: Scale for Continuous Data

Constructs	**Item**	**Measurement**	**Coding**

Perceived Pleasure Anthropomorphism Functional Informational Perceived Knowledge Perceived Benefit Affective Trust Cognitive Trust User Acceptance	3	5-point Likert scale	1= Strongly Disagree 2= Disagree 3= Neutral 4= Agree 5= Strongly Agree
Risk Tolerance	13	Total score range = 0–47	0–18: Low 19–22: Below-average 23–28: Moderate 29–32: Above-average 33–47: High

Source: Developed for the research

3.6 Common Method Bias

Common Method Bias (CMB) refers to variance that is attributable to the measurement method rather than to the constructs being measured. It is a common concern in studies that rely on self-reported, single-source, cross-sectional survey data, as it may artificially inflate or deflate observed relationships between variables (Podsakoff et al., 2003). Since this study collected data using a single structured questionnaire administered to Gen Z respondents in Malaysia, steps were taken to minimise the risk of CMB through both statistical and procedural approaches.

3.6.1 Statistical Approach

The study employed the full collinearity assessment approach to test for CMB in the Partial Least Squares Structural Equation Modeling (PLS-SEM) framework. Following Kock's (2015) guidelines, all constructs in the model were assessed for variance inflation factors (VIFs). If all latent constructs have VIF values below 3.3, the model can be considered free of severe common method bias.

This approach is better than the traditional Harman's single-factor test. It accounts for both vertical and lateral collinearity (Kock, 2015). Previous studies show that the full collinearity test identifies CMB effectively and is widely used in management, marketing, and technology adoption research (Chin et al., 2012). In this study, the VIF values for all constructs were below 3.3, showing that CMB does not affect the results.

3.6.2 Procedural Approach

To reduce common-method bias, several steps were taken during questionnaire design. Respondents were assured of anonymity and confidentiality. Items were written in clear, neutral language. A balanced five-point Likert scale was used to reduce acquiescence bias. These steps, together with statistical checks, strengthened the study's validity.

3.7 Pre-Testing and Pilot Test

Before distributing the final questionnaire, pre-testing and a pilot study were conducted to ensured clarity, reliability, and appropriate of the measurement items.

The pre-test involved expert validation. Two lecturers from the Faculty of Accountancy and Management (FAM) at Universiti Tunku Abdul Rahman (UTAR) reviewed the questionnaire. They focused on content validity, clarity of wording, and alignment with the constructs. Minor revisions were made, such as simplifying technical terms and rephrasing complex items to improve understanding. The revised questionnaire was given to five respondents to ensure the questions were clear, unambiguous, and not confusing.

After the pre-test, a pilot test was conducted with 31 Gen Z respondents in Malaysia who had similar characteristics to the target population. Reliability tests were conducted using the pilot test data, and the result were shown in Table 3.4. Cronbach's Alpha for all constructs were above the threshold of 0.700, which means that all constructs are reliable.

Table 3.4 Reliability Test

Constructs	**Cronbach's Alpha**
Perceived Pleasure	0.915
Anthropomorphism	0.767
Functional	0.852
Informational	0.904
Perceived Knowledge	0.700
Perceived Benefit	0.807
Affective Trust	0.740
Cognitive Trust	0.819
User Acceptance	0.881

Source: Developed for the research

3.8 Data Collection

Data were collected using a self-administered online questionnaire. The questionnaire was distributed through social media platforms such as WhatsApp, Facebook, and RedNote. Online distribution was chosen because it is effective to reached Malaysian Gen Z that appropriate for this study.

Before responding, participants were informed the study's objectives. Following the practices by Ruhani et al. (2024), respondents were assured of anonymity and confidentiality. They were also told that participation was voluntary. This study used purposive sampling, targeting Gen Z individuals with different levels of investment experience and awareness of robo-advisors.

3.9 Data Analysis

3.9.1 Data Screening

Completed responses were screened for accuracy and completeness, invalid cases removed. The final dataset was prepared for analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM), a common method in behavioural and technology research (Amaro et al., 2015).

Data screening ensured the dataset was accurate, consistent, and ready for analysis. This process included checking for outliers, duplicate entries, and inconsistent responses. Removing outliers improve the reliability of PLS-SEM analysis because extreme values do not bias the results (Yusuf Haji-Othman et al., 2024).

3.9.2 Data Coding

All categorical variables were converted to numerical codes for statistical analysis. For example, gender was coded as 1 = Male and 2 = Female. This approach makes data entry easier and allows effective analysis in SmartPLS, following best practices in quantitative survey research (Purwanto & Sudargini, 2021).

3.9.3 Questionnaire Checking

The questionnaires were checked for completeness before final data entry. Incomplete and apparent contradiction responses were removed, ensuring that only valid and reliable responses were included in the analysis. Clean data is a basic requirement in PLS-SEM studies because invalid cases can affect both the measurement and structural model (Ghasemy et al., 2020).

3.9.4 Data Editing

After screening and coding, data editing was carried out to fix entry errors and to ensure the data format was consistent. This included aligning scales across all constructs, such as ensuring all Likert items were coded consistently from 1 = Strongly Disagree to 5 = Strongly Agree. Data editing also included standardizing answers in open-ended demographic fields. These steps improved data accuracy and reduced errors before conducting statistical analysis.

3.9.5 Missing Value

Missing values often occurred in survey research. This study removed responses with many missing values. For responses with few missing values, the mean replacement method was used, it is a common method in PLS-SEM research (Amusa & Hossana, 2024). This approach maintains the dataset intact without significantly reducing the sample size. This approach follows common PLS-SEM guidelines that stress careful handling of missing data to keep the model valid (Yusuf Haji-Othman et al., 2024).

3.10 Data Testing

3.10.1 Descriptive Analysis

Descriptive analysis was used to summarise respondents' demographic characteristics and provide an overview of the dataset. This included frequencies, percentages, means, and standard deviations for variables. Descriptive statistics help to profile respondents and ensure the sample reflects the target population (Naini & Reddy, 2023). Descriptive results for the main constructs provided an initial understanding of respondents' perceptions before hypothesis testing.

3.10.2 Inferential Analysis

Inferential analysis was used to test the hypothesised relationships among constructs using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS. Predictive research, complex models, and non-normally distributed dataset are all suitable for PLS-SEM (Hair et al., 2019). The inferential analysis was carried out in three stages:

1. **Measurement Model**

Reliability was tested using Cronbach's alpha and Composite Reliability (CR), with thresholds above 0.70. Convergent validity was confirmed when the Average Variance Extracted (AVE) was above 0.50. Discriminant validity was tested using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio (Hair et al., 2021).

2. **Structural Model**

The structural model was tested after the measurement model was confirmed. Path coefficients, t-values, and p-values were obtained using bootstrapping with 5,000 subsamples. Predictive power was assessed using R^2 values for endogenous constructs, effect sizes (f^2) and predictive relevance (Q^2) were also examined (Hizam et al., 2022).

3. **ANOVA**

Respondents risk tolerance was tested using ANOVA test. Homogeneity of Variances Test (Levene's) was carried out to test the populations variances for each group. ANOVA was also used to examine the difference between respondents' risk tolerance group.

3.11 Chapter Summary

This chapter described the research methodology, including research design, sampling, and instrument development. The clarity and reliability of the questionnaire were ensured through pre-testing and a pilot study. Data collection and preparation included screening, coding, checking, editing, and handling missing values. Data testing was conducted using descriptive statistics to profile respondents and inferential analysis with PLS-SEM in SmartPLS. Finally, ANOVA was introduced to compare structural relationships across subgroups, particularly by risk tolerance, thereby strengthening the robustness of the study's findings.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter explains the data analysis and the results of the PLS-SEM model. Data analysis was conducted using SmartPLS 4. Questionnaires were collected from 28 August 2025 to 22 November 2025. Data cleaning was done before the analysis started.

4.1 Data Screening and Data Cleaning

Before analysis started, the dataset was screened for completeness, normality, and outliers. All questionnaires with non-engaged patterns were removed. After data cleaning, 273 valid responses remained.

4.2 Common Method Bias

4.2.1 Full Collinearity Test

This study used full collinearity test and a Harman Single Factor Test to check for common method bias. The result is shown in Table 4.1. According to Kock (2015), VIF values above 3.3 may indicate pathological collinearity; values below 3.3 suggest no serious common-method bias. In the present model, the VIFs of all variables were below 3.3; thus, there is no common-method bias.

Table 4.1: Full Collinearity Test

CONSTRUCTS	VIF
PP	1.550
AN	1.423
FN	1.758
IN	1.853
PK	1.451
PB	1.822
AT	1.904
CT	1.843
UA	1.758

Source: Developed for the research

4.2.2 Harman Single Factor Test

This study also conducted the Harman Single Factor Test to detect common method bias. The result is shown in Table 4.2. If the variance percentage exceeds 50%, common method bias may be present (Podsakoff et al., 2003). Based on the Harman Single-Factor Test, the variance accounted for was below 50%, indicating no common-method bias.

Table 4.2: Harman Single Factor Test

Harman Single Factor Test
Total Variance Explained by a Single Factor:
29.4%

Source: Developed for the research

4.3 Descriptive Data Analysis

4.3.1 Respondent Profile

This section discusses the demographic profile of all respondents. The results are shown in Table 4.3.

Table 4.3: Respondent Profile

Constructs	Frequency	% of Column Total
Age		
18-21	110	40.44%
22-24	102	37.50%
25-28	60	22.06%
Gender		
Male	94	34.56%
Female	178	65.44%
State		
Johor	36	13.24%
Kedah	11	4.04%
Kelantan	4	1.47%
Melaka	11	4.04%
Negeri Sembilan	21	7.72%
Pahang	8	2.94%
Perak	17	6.25%
Perlis	4	1.47%
Pulau Pinang	12	4.41%
Sabah	10	3.68%
Sarawak	12	4.41%
Selangor	120	44.12%
Terengganu	6	2.21%

Education Level		
Secondary school	6	2.21%
Pre-university / Diploma / Foundation	45	16.54%
Bachelor's degree	204	75.00%
Master's degree	17	6.25%
Money Income Range		
Less than RM2,000	154	56.62%
RM2,000 – RM3,999	62	22.79%
RM4,000 – RM5,999	35	12.87%
RM6,000 – RM7,999	11	4.04%
RM8,000 – RM9,999	4	1.47%
RM10,000 and above	6	2.21%
How many years have you been actively investing?		
No experience	112	41.18%
Less than 1 year	92	33.82%
1–3 years	57	20.96%
4–7 years	7	2.58%
8–15 years	3	1.11%
more than 15 years	1	0.37%
Have you ever used a robo-advisory service before?		
Yes	137	50.37%
No	135	49.63%
Level of Agentic AI understanding		
None	47	17.28%
Basic	170	62.50%
Intermediate	49	18.01%
Advanced	6	2.21%
General perception of Agentic AI robo-advisor replacing a human financial advisor		
Very Negative	9	3.31%
Negative	33	12.13%
Neutral	65	23.90%
Positive	154	56.62%
Very Positive	11	4.04%

Source: Developed for the research

Based on Table 4.3, the majority of respondents were between 18 and 21 years old (40.44%), followed by those aged 22–24 (37.50%), while respondents aged 25–28 accounted for 22.06%. Regarding gender distribution, female respondents formed the larger proportion of the sample (65.44%), whereas male respondents accounted for 34.56%.

Regarding geographical distribution, most respondents were from Selangor (44.12%), followed by Johor (13.24%) and Negeri Sembilan (7.72%). The remaining respondents were distributed across other Malaysian states in smaller numbers, showing a diverse geographic spread. Regarding education level, majority of respondents held a bachelor's degree (75.00%), indicating that they were well-educated and knowledgeable.

For monthly income, more than half of the respondents earned less than RM2,000 (56.62%). Respondents earning between RM2,000 and RM3,999 made up 22.79%. The proportion of higher income groups is relatively small compared to other groups. For investment experience, 41.18% of respondents reported no investment experience. Respondents with less than one year of experience made up 33.82%. 20.96% of respondents had one to three years of investment experience. Respondents with more than four years of experience made up a very small proportion of the sample.

50.37% of respondents reported that they had used robo-advisory services before. Most respondents reported a basic level understanding in agentic AI (62.50%). Respondents did no understanding at all made up to 17.28%, followed by those with intermediate understanding (18.01%). Only 2.21% of respondents had an advanced understanding in it. For views on agentic AI robo-advisors replacing human financial advisors, 56.62% of respondents reported a positive view. Negative and very negative perceptions together accounted for 15.44%, indicating that overall attitudes toward agentic AI robo-advisors were generally favorable.

4.4 Partial Least Square Structural Equation Modelling

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyse and interpret the data. The two-step PLS-SEM procedure was followed. First, evaluate the measurement model, then evaluate the structural model.

4.5 Measurement Model Assessment

4.5.1 Convergent Validity

The measurement model was assessed by testing the reliability and validity of each construct. The assessment of the measurement model is shown in Table 4.4.

Table 4.4: Convergent Validity

Constructs	Factor Loadings (F.L)	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
AN	0.840 0.854 0.835	0.796	0.797	0.880	0.711
AT	0.873 0.776 0.830	0.772	0.802	0.867	0.685
CT	0.790 0.781 0.740	0.660	0.665	0.814	0.594
FN	0.850 0.800 0.757	0.723	0.730	0.844	0.645

IN	0.812 0.730 0.782	0.669	0.674	0.819	0.601
PB	0.850 0.771 0.779	0.720	0.727	0.843	0.641
PK	0.846 0.900 0.885	0.850	0.855	0.909	0.769
PP	0.650 0.634 0.876	0.585	0.700	0.768	0.530
UA	0.795 0.777 0.837	0.727	0.737	0.845	0.646

Source: Developed for the research

Factor loadings for most of the constructs were above the threshold of 0.70, indicating a strong relationship between each indicator and its respective constructs. Only PP has two-factor loadings at 0.650 and 0.634, which are slightly below 0.70 but still acceptable.

Cronbach's Alpha for most of the constructs were above 0.60, indicating moderate to high internal consistency and reliability. Only the PP has a slightly lower Cronbach's Alpha of 0.585.

rho_A for most of the constructs was above 0.70, which exceeded the recommended minimum of 0.70 for most constructs. Only CT and IN have slightly lower rho_A values of 0.665 and 0.674. This shows that the construct reliability is adequate.

Composite Reliability for all constructs is above 0.70. Composite Reliability is a more accurate reliability measure in PLS-SEM. These results show that each construct has good internal consistency.

AVE of all the constructs is above the threshold of 0.50. This indicates that each construct explains more than half of the variance of its indicators, confirming convergent validity.

4.5.2 Discriminant Validity

To test the model's discriminant validity, this study evaluated it using the Fornell-Larcker criterion and the HTMT method. Discriminant validity refers to the fact that constructs are empirically distinct. The results are shown in Table 4.5 and Table 4.6.

Table 4.5: Fornell-Larcker

Fornell-Larcker criterion

Construct	**AN**	**AT**	**CT**	**FN**	**IN**	**PB**	**PK**	**PP**	**UA**
AN	**0.843**								
AT	0.485	**0.827**							
CT	0.396	0.533	**0.771**						
FN	0.294	0.348	0.436	**0.803**					
IN	0.327	0.406	0.514	0.573	**0.775**				
PB	0.380	0.465	0.512	0.502	0.523	**0.801**			
PK	0.355	0.497	0.417	0.328	0.355	0.365	**0.877**		
PP	0.357	0.398	0.475	0.456	0.403	0.473	0.336	**0.728**	
UA	0.400	0.551	0.498	0.417	0.481	0.499	0.386	0.409	**0.803**

Source: Developed for the research

Table 4.6: HTMT

HTMT

Construct	**AN**	**AT**	**CT**	**FN**	**IN**	**PB**	**PK**	**PP**	**UA**
AN									
AT	0.608								

CT	0.542	0.730						
FN	0.384	0.466	0.629					
IN	0.451	0.553	0.775	0.822				
PB	0.506	0.605	0.734	0.698	0.754			
PK	0.426	0.614	0.549	0.415	0.464	0.466		
PP	0.498	0.516	0.732	0.738	0.634	0.719	0.469	
UA	0.519	0.717	0.701	0.582	0.682	0.682	0.494	0.618

Source: Developed for the research

Table 4.5 shows that the Fornell–Larcker criterion values for each construct exceeded its correlations with all other constructs, satisfying the Fornell–Larcker rule. Meanwhile, Table 4.6 shows that all HTMT values are below the conservative threshold of 0.85. Thus, both results concluded that discriminant validity has been successfully established.

4.6 Structural Model Assessment

After assessing the measurement model, this study proceeded to the structural model assessment. Before assessing the structural model, the VIFs were examined to assess multicollinearity among the variables. As shown in Table 4.7, all VIF values were below the threshold of 3.3, indicating no multicollinearity issue in this model.

Table 4.7: Structural Model

Construct	**VIF**
AN	1.146
AT	1.396
CT	1.396
FN	1.643
IN	1.709
PB	1.557

PK	1.219
PP	1.146

Source: Developed for the research

4.6.1 PLS Estimation

This study conducted PLS Estimation to evaluate the structural relationships among the constructs in the research model. The results are shown in Table 4.8.

Table 4.8: PLS Estimation

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Bias	5.0% CI	95.0% CI
AT → UA	0.400	0.402	0.061	6.503	0.000	0.002	0.291	0.494
CT → UA	0.285	0.287	0.067	4.258	0.000	0.002	0.172	0.392
PP → AT	0.258	0.265	0.062	4.127	0.000	0.007	0.143	0.351
AN → AT	0.393	0.394	0.065	6.055	0.000	0.001	0.287	0.501
FN → CT	0.095	0.100	0.076	1.253	0.105	0.005	-0.032	0.217

IN → CT	0.253	0.251	0.082	3.084	0.001	-0.002	0.126	0.394
PK → CT	0.202	0.204	0.064	3.140	0.001	0.002	0.100	0.310
PB → CT	0.258	0.260	0.075	3.449	0.000	0.002	0.135	0.380

Source: Developed for the research

The path coefficient results indicate which hypotheses are supported based on the T-statistics and p-values (significance level = 0.05). In addition, a path is considered significant if the confidence interval does not include zero. According to Table 4.8, all paths are significant except hypothesis H5.

Hypothesis H1 examined the relationship between Affective Trust and User Acceptance. Table 4.8 shows a t-value of 6.055 and a p-value of 0.000, indicating strong statistical significance. The 95% confidence interval is 0.291-0.494, which does not include 0, further confirming the significance of this relationship.

Hypothesis H2 examined the relationship between Cognitive Trust and User Acceptance. Table 4.8 shows a t-value of 4.258 and a p-value of 0.000, indicating strong statistical significance. The 95% confidence interval is 0.172-0.392, which does not include 0, further confirming the significance of this relationship.

Hypothesis H3 examined the relationship between Perceived Pleasure and Affective Trust. Table 4.8 shows a t-value of 4.127 and a p-value of 0.000, indicating strong statistical significance. The 95% confidence interval is 0.143-0.351, which does not include 0, further confirming the significance of this relationship.

Hypothesis H4 examined the relationship between Anthropomorphism and Affective Trust. Table 4.8 shows a t-value of 6.503 and a p-value of 0.000, indicating strong statistical significance. The 95% confidence interval is 0.287-0.501, which does not include 0, further confirming the significance of this relationship.

Hypothesis H5 examined the relationship between Functional and Cognitive Trust. Table 4.8 shows a t-value of 1.253 and a p-value of 0.105, indicating that it is not statistically significant. The 95% confidence interval is -0.032-0.217, which include 0, further confirming the lack of significance of this relationship.

Hypothesis H6 examined the relationship between Informational and Cognitive Trust. Table 4.8 shows a t-value of 3.084 and a p-value of 0.001, indicating strong statistical significance. The 95% confidence interval is 0.126-0.394, which does not include 0, further confirming the significance of this relationship.

Hypothesis H7 examined the relationship between Perceived Knowledge and Cognitive Trust. Table 4.8 shows a t-value of 3.140 and a p-value of 0.001, indicating strong statistical significance. The 95% confidence interval is 0.100-0.310, which does not include 0, further confirming the significance of this relationship.

Lastly, hypothesis H8 examined the relationship between Perceived Benefit and Cognitive Trust. Table 4.8 shows a t-value of 3.449 and a p-value of 0.000, indicating strong statistical significance. The 95% confidence interval is 0.135-0.380, which does not include 0, further confirming the significance of this relationship.

4.7 Coefficient of Determination (R2)

To evaluate the inner model assessment, this study analysed the determination coefficient R^2 and the adjusted R^2. According to Chin (1998), R^2 values of 0.67 indicate high explanatory power, 0.33 indicate moderate explanatory power, and 0.19 indicate weak explanatory power. The results are shown in Table 4.9.

Table 4.9: Adjusted R^2

Constructs	R Square	R Square Adjusted
AT	0.294	0.288
CT	0.388	0.379
UA	0.362	0.357

Source: Developed for the research

From Table 4.9, the R^2 value for AT falls in the weak range, suggesting weak explanatory power; while the R^2 value for CT and UA falls in the moderate range, suggesting moderate explanatory power.

4.8 Effect Size (f^2) and Predictive Relevance (Q^2)

Next, this study uses f^2 effect size and Q^2 predictive relevance to evaluate the practical significance and predictive power of this structural model. The results are shown in Table 4.10 and Table 4.11.

4.8.1 Effect Size (f^2)

According to Cohen (1988), f^2 values less than 0.02 indicate no effect, 0.02–0.149 indicate a small effect, 0.15–0.349 indicate a medium effect, and values greater than 0.35 indicate a large effect. From Table 4.10, AN has a medium effect on AT with $f^2 = 0.191$, and AT also has a

medium effect on UA with $f^2 = 0.179$. Most variables have small effects on their endogenous constructs, except for FN on CT, which shows no effect ($f^2 = 0.009$).

Table 4.10: Effect Size (f^2)

Effect Size (f^2)

Predictor → Outcome	**AT**	**CT**	**UA**
AN	0.191		
PP	0.082		
FN		0.009	
IN		0.061	
PB		0.070	
PK		0.055	
AT			0.179
CT			0.091
UA			

Source: Developed for the research

4.8.2 Predictive Relevance (Q^2)

A Q^2 value greater than zero indicates that the model has predictive relevance for that specific endogenous construct, meaning it predicts the indicator data points better than simply using the average (mean) value. A Q^2 value less than zero suggests a lack of predictive relevance, possibly indicating a weak structural or measurement model or overfitting. From Table 4.11, all endogenous constructs, AT, CT, and UA, have Q^2 values greater than zero, with CT showing the highest predictive relevance with 0.351. This indicated that the model can reasonably predict outcomes for all key endogenous variables, supporting its generalizability beyond the sample data.

Table 4.11: predictive Relevance (Q^2)

Predictive Relevance (Q^2)

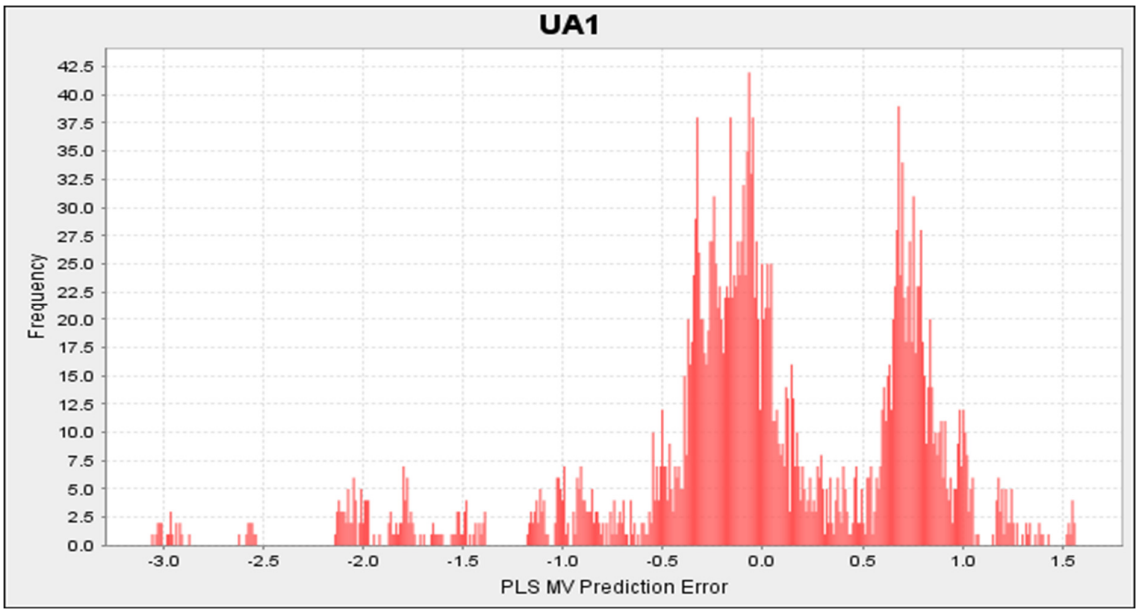
Endogenous Construct	RMSE	MAE	Q^2predict
AT	0.863	0.636	0.270
CT	0.817	0.603	0.351
UA	0.852	0.618	0.290

Source: Developed for the research

4.9 PLSpredict Assessment

This study conducted PLSpredict to evaluate the out-of-sample predictive power. Since all Q^2 values are greater than zero, the next step is to compare RMSE (or MAE) values with the naive LM benchmark (Shmueli et al., 2019). According to Shmueli et al. (2019), the distribution of prediction errors should be examined before deciding between RMSE and MAE. RMSE is recommended when the distribution of prediction errors is symmetrical, while MAE is recommended when the distribution of prediction errors is non-symmetric. Figure 4.1 shows the PLS-SEM MV error histogram. It suggests that all the distributions of prediction errors are symmetrical. Therefore, RMSE is chosen.

Figure 4.1: PLS Predict



Source: Developed for the research

Table 4.12: PLS Predict

Indicator	PLS RMSE	PLS MAE	LM RMSE	LM MAE	RMSE Diff (PLS–LM)	MAE Diff (PLS–LM)
AT1	0.806	0.615	0.784	0.602	0.022	0.013
AT2	0.846	0.616	0.866	0.622	–0.020	–0.007
AT3	0.877	0.675	0.827	0.645	0.050	0.030
CT3	0.646	0.519	0.629	0.563	0.017	–0.005
CT2	0.643	0.502	0.654	0.501	–0.011	0.001
CT1	0.702	0.505	0.667	0.513	0.035	–0.008
UA1	0.747	0.541	0.755	0.566	–0.008	–0.025
UA3	0.824	0.630	0.809	0.624	0.015	0.006
UA2	0.763	0.571	0.810	0.626	–0.047	–0.055

Source: Developed for the research

As shown in Table 4.12, the MAE Diff (PLS-LM) is negative for most indicators. The procedure compares the PLS-SEM model's prediction error with that of a benchmark linear model (LM). According to Shmueli et al. (2019), a model had moderate predictive power, with most indicators showing negative differences in the PLS–LM.

4.10 Chapter Summary

This chapter presents the results of PLS-SEM data analysis using SMARTPLS 4. After data screening and cleaning, common-method bias was examined using full collinearity tests and Harman's single-factor test; the results indicated no common-method bias. Descriptive analysis was conducted to understand the demographic profile of all respondents. The results of the measurement and structural models indicated that most of the hypotheses were supported, except for hypothesis H5, Functional to Cognitive Trust. The model also demonstrated acceptable explanatory and predictive power, as indicated by R^2 and PLSpredict outcomes. Key factors influencing users' trust and acceptance of agentic AI robo-advisory services are highlighted by these findings.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter discusses the findings of this study by comparing them with past literature on AI trust, human AI interaction, and robo-advisory services. This chapter also illustrates the theoretical and practical implications, limitations of the study, and future research recommendations.

5.1 Discussion of Major Findings

This study examined the relationships between agentic AI attributes (hedonic, heuristic, utilitarian, and systematic) and trust (affective and cognitive). It also examined how these factors influence user acceptance of agentic AI robo-advisory systems. The results are shown in Table 5.1.

Table 5.1: Major Findings

HYPOTHESIS	RELATIONSHIP	RESULT
H1	AT → UA	Supported
H2	CT → UA	Supported
H3	PP → AT	Supported
H4	AN → AT	Supported
H5	FN → CT	Not Supported
H6	IN → CT	Supported
H7	PK → CT	Supported

H8	PB → CT	Supported

Source: Developed for the research

5.1.1 Affective Trust (AT) and User Acceptance (UA)

Hypothesis 1 (H1) was supported. This result is consistent with previous research such as Hildebrand and Bergner (2021). Affective trust plays an important role in user acceptance of AI-based services. AI interventions were found to have higher acceptance with higher emotional trust gained (Kyung and Kwon, 2022). Pathak and Bansal (2024) also found that affective trust in AI agents increases users' intention to adopt them. The higher a user's affective trust level in AI agents, the stronger their willingness to adopt it.

This finding suggested that users are more likely to adopt the AI if they feel emotionally comfortable with it. This happens because affective trust reduces emotional uncertainty and helps users feel safe and secure when following AI advice. Users often feel stress and worry in financial decisions. Emotional reassurance becomes very important in this context. Users' affective trust therefore positively influences user acceptance of Agentic AI robo-advisors.

5.1.2 Cognitive Trust (CT) and User Acceptance (UA)

Hypothesis 2 (H2) was supported. This finding is consistent with previous research such as Pathak and Bansal (2024). Shamim et al. (2023) showed that AI features like reliability and functionality increase users' cognitive trust. Indicated that greater cognitive trust is contributed to higher trust and acceptance of AI systems.

This finding show that users are more likely to use an AI robo-advisor when they see it as competent, reliable, and accurate. Financial decisions require strong confidence in system

performance. Users who believe that agentic AI robo-advisors provide clear and logical advice are more willing to adopt it. Users' cognitive trust therefore positively influences user acceptance of Agentic AI robo-advisors.

5.1.3 Perceived Pleasure (PP) and Affective Trust (AT)

Hypothesis 3 (H3) was supported. The results show that perceived pleasure has a positive effect on affective trust. This result aligns with previous research by Ding and Najaf (2024). van Pinxteren et al. (2019) found that enjoyable interaction with AI service agents increases users' emotional trust. In situations with high uncertainty, such as financial decisions, pleasant interaction helps users feel calmer and more comfortable when using AI. Kurniawan and Tankoma (2023) studied an online food delivery system and found that enjoyment from using the system strongly increased user emotional trust. When users enjoyed the interaction, their emotional trust in the system increased. This indicates that users' affective trust will increase by adding pleasant features in agentic AI robo-advisory system increase.

This finding suggests that users who enjoy interacting with agentic AI robo-advisors tend to have higher affective trust. During financial decision-making, a positive experience can reduce worry and help users feel more comfortable and emotionally connected. Thus, users perceived pleasure positively influence affective trust of agentic AI robo-advisory system.

5.1.4 Anthropomorphism (AN) and Affective Trust (AT)

Hypothesis 4 (H4) was supported. This result is consistent with previous research such as Chi and Vu (2022). The results indicate that human-like features in AI robo-advisors significantly influence users trust. Ma et al. (2025) found that chatbots with human-like features increased perceived empathy and trust. Their research shown that the higher the level of human-like design, the higher the level of trust. Shi et al. (2025) found that human-like features, such as

emoticons increased user affective trust in AI agents. In their experiment, human-like features positively affected trust. These results show that users' affective trust increases when the design of agentic AI robo-advisory systems is human-like.

This finding suggest that anthropomorphism reduces the mental gap between users and AI., Users tend to trust agentic AI robo-advisor more and more open to its advice when users perceived it as social partner rather than purely technical tool. Thus, anthropomorphism positively influences affective trust of agentic AI robo-advisors.

5.1.5 Functional (FN) and Cognitive Trust (CT)

Hypothesis 5 (H5) was not supported. This contradicting with previous research such as Maier et al. (2022). This result may be due to Gen Z is digital native cohort that actively use digital finance products such as e-wallet and mobile banking. The agentic AI advisory systems are designed for decision-making and automate related tasks, people are assumed it to perform the tasks. Thus, Gen Z take this as granted, resulting to insignificantly impact on the cognitive trust. Zhang et al. (2018) argued that technical functions have weaker or no effect on trust because users already expect AI systems to work efficiently. Users trust and adopt AI because of what it helps them to achieve, not because of how it works. Fischer & Schellenbach (2025) stated that mere functional alone may not increase cognitive trust, it required to going beyond the functional to build trust.

This finding suggest that Gen Z and young adult users already expect digital systems to function well. They build cognitive trust based on higher-level features like informational, perceived benefits, and perceived knowledge. Functional alone does not increase cognitive trust in agentic AI robo-advisors.

5.1.6 Informational (IN) and Cognitive Trust (CT)

Hypothesis 6 (H6) was supported. Consistent with previous researh such as Belanche et al. (2019. Liu et al. (2025) found that higher information quality improves users' perceived expertise and builds cognitive trust in AI. Radiansyah et al. (2023) found that clear and accurate information is associated to greater cognitive trust. Users' cognitive trust improved by the transparent and useful information provided by agentic AI robo-advisory systems.

When users see AI-generated information as, they are more likely to trust it. Users rely on clarity and justification to judge reliability when making financial decisions. Clear explanations and transparent data increase confidence in the competence and accuracy of agentic AI robo-advisory systems. Thus, informational positively affects cognitive trust in Agentic AI robo-advisors.

5.1.7 Perceived Knowledge (PK) and Cognitive Trust (CT)

Hypothesis 7 (H7) was supported. This aligns with previous research such as Yi et al. (2023). Gursoy et al. (2019) found that users can better evaluate system outputs when they think they know about the AI systems, which strengthens their cognitive trust. Knowledge reduces uncertainty and helps users assess AI recommendations more carefully and confidently. Liu et al. (2025) showed that understanding the AI provided information can improves perceived expertise and credibility of the AI, thereby increasing trust. When users feel informed, they trust AI recommendations based on rational reasoning rather than blind reliance. Alruwaili et al. (2025) reported that users' familiarity with AI is the strongest predictor of trust. Users with more AI knowledge consistently expressed greater trust in AI systems. Thus, it suggests that users with higher perceived knowledge tend to develop greater cognitive trust.

The findings suggest that users are more likely to develop cognitive trust when they understand how the AI or investment process works. Knowledge reduces uncertainty and helps users

interpret AI recommendations more accurately, boosting confidence in the system's credibility and competence. Thus, users perceived knowledge positively influences cognitive trust in Agentic AI robo-advisors.

5.1.8 Perceived Benefit (PB) and Cognitive Trust (CT)

Hypothesis 8 (H8) was supported. This aligns with previous research such as Sabir et al. (2023). Shamim et al. (2023) found that helpful results generated by AI strengthen cognitive trust, which means users perceived benefits from AI increase cognitive trust. Pathak and Bansal (2025) also found that perceived usefulness and quality of AI systems increase cognitive trust. In their model, perceived AI quality positively affects cognitive trust. This indicates that users' cognitive trust of agentic AI robo-advisory system increases when they perceive more benefits or capabilities in it.

This finding suggests that users develop strong cognitive trust when they perceive meaningful benefits such as accurate suggestions or time savings from an agentic AI robo-advisor. Users evaluate these benefits as evidence of the AI's reliability and capability, which increases their confidence in using it. Thus, users perceived benefits positively influences cognitive trust in agentic AI robo-advisors.

5.2 Implications of the Study

5.2.1 Theoretical Implications

This research makes significant theoretical contributions to the study of user acceptance of agentic AI robo-advisory systems. The study first confirmed the dual-path model of trust in the context of Agentic AI robo-advisory services, showing that both affective and cognitive trust were important antecedents of user acceptance. This finding extends AI trust theories by

showing that user acceptance of financial robo-advisors results from two different dimensions of trust. In particular, perceived pleasure and anthropomorphism design were found to significantly enhance affective trust, while informational, perceived knowledge, and perceived benefit were found to be important drivers of cognitive trust. By identifying these specific antecedents, this study enriches traditional trust models.

Moreover, the lack of a significant effect of the functional factors on cognitive trust also challenges classical theories such as the TAM and UTAUT. In the context of AI robo-advisors, functionality alone could not establish cognitive trust among users. This may indicate that for Gen Z users, specifically so-called digital natives, the experiential and value-related factors (enjoyment, trust-building explanations, and clear benefits) may be more important than mere functionality. The theoretical implications are that, regarding the diffusion of AI-based financial services, trust formation should be understood as a dual-path mechanism encompassing both affective engagement and cognitive evaluation, and that established models need to be adapted to account for these additional factors.

5.2.2 Practical Implications

The practical implications of these findings are to provide guidelines for fintech app developers to design more intuitive, transparent, and trustworthy agentic AI robo-advisors. First, given the strong increase in affective trust due to perceived pleasure, system developers should focus on creating smooth, intuitive, and enjoyable user experiences. User interfaces that respond quickly, provide clear feedback, and make interactions pleasant can create a sense of enjoyment in users and thus foster emotional trust.

Furthermore, anthropomorphic design cues strengthen the emotional connection to the system. Examples include the use of conversational natural language, empathetic greetings or messages, and optional humanlike avatars or voices, thus making the AI advisor more personable and appealing. In line with the finding that anthropomorphic features significantly improve affective trust, designers can leverage these features to humanise the interface.

Although functional did not significantly influence cognitive trust among the Gen Z group, it may still be important for other generations or less digitally experienced users. Therefore, service providers should ensure smooth, reliable system performance as a basic requirement, while prioritising transparency and clear communication of benefits to build trust. Emphasizing explainable recommendations, user education, and value-driven outcomes can strengthen trust across diverse user groups with different levels of technological familiarity.

Providing clear information is crucial for agentic AI robo-advisory systems as it supports cognitive trust development. Practical steps include clear explanation panels, a risk rationale, and simple summaries that show how AI generates recommendations. These features reduce uncertainty and increase users' confidence in the system. Furthermore, educational support tools such as tutorials, help videos, tooltips, or step-by-step onboarding modules can increase users' perceived knowledge and competence. This aligns with the finding that user knowledge improves cognitive trust. The system should also clearly show the benefits and value it provides. Highlighting benefits such as low advisory costs, personalised investment suggestions, and successful performance examples strengthen users' belief in the system’s usefulness and reinforce cognitive trust.

The system should be designed to make users feel reassured and enjoyable, with human-like features, to build affective trust. Confirmations and positive feedback should be given, and advice should be framed empathetically. These measures make users feel safe and encourage by reducing their anxiety. At the same time, cognitive trust is strengthened by making the system accurate, consistent, and transparent. Practical steps include testing the algorithm, showing past performance results, and keeping recommendation logic consistent. Focusing on both emotional support and technical credibility helps design strategies that build user trust and increase acceptance of agentic AI robo-advisory services.

5.3 Limitations of the Study

This study has some limitations. The generalizability of findings is limited by the sample. The participants may not fully represent a broader investor population in terms of age, location, or financial literacy. This limits how the results apply to other user groups or cultural contexts.

This research collected data at one point in time in this cross-sectional research design. We cannot identify causal effects or changes in trust and acceptance that may happen with longer use of a robo-advisor. Trust can change with experience, making the one-time survey only reflects a snapshot of attitudes.

This study did not deeply examine into some important personal and contextual factors that may affect trust in financial technology. Variables like user risk tolerance, prior investment experience, or market conditions were not included. These factors may change how users view and trust an agentic AI robo-advisor.

In summary, this research provides valuable insights into trust in agentic AI robo-advisory systems. However, this finding need to be viewed in the light of these limitations.

5.4 Recommendations for Future Research

This study suggests several directions for future research. Longitudinal or experimental designs can use in future study to clearly observe how trust in robo-advisory systems develops over time and to identify causal links. A longitudinal panel can show whether the effects of perceived pleasure, anthropomorphism, and other factors on trust stay the same or change as users interact more with the AI advisor.

The conceptual model could be extended by adding more constructs that are related to AI trust. For example, future research may include measures of transparency, fairness, perceived risk, or explainability to capture other dimensions that may affect user trust in AI.

Researchers can study how different AI advisory systems affect user experiences. For instance, comparing fully automated AI advisors with hybrid systems that include human oversight. Similarly, interface styles can range from simple and task-focused designs to more human-like and social designs. This can help explain how interface design affect trust and use.

Future studies can move beyond self-reported intentions and examine actual user behavior. Researchers can collect data of use frequency, user retention rates, or actual investment performance. Study of actual usage would provide much stronger evidence of how trust leads into real-world usage and effectiveness for agentic AI robo-advisory systems. These are promising directions for scholars to take the next steps in this study and fully understand and predict user trust.

5.5 Chapter Summary

This study used a dual-path model to examine factors that influence user acceptance of agentic AI robo-advisory services. The findings show that affective trust and cognitive trust play an important role in shaping user acceptance of agentic AI. Perceived pleasure and anthropomorphism increased affective trust, while informational factors, perceived knowledge, and perceived benefits increased cognitive trust. Functional factors did not show a significant effect on cognitive trust, which suggests that technical performance alone is not enough to build cognitive trust in agentic AI systems. Despite these findings, this study has several limitations. Therefore, future research is recommended to explore additional factors and contexts further to deepen understanding of trust formation and the adoption of agentic AI technologies.

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Appendices

Appendix 1.0: Questionnaire

Section 1:

The purpose of this study is to understand how people in Malaysia perceive and accept AI-powered robo-advisory services in financial decision-making. Specifically, the study examines how enjoyment (hedonic), functionality (utilitarian), and systematic processing of information influence trust (both affective and cognitive), risk tolerance, and ultimately, user acceptance of such technologies.

What is Agentic AI?

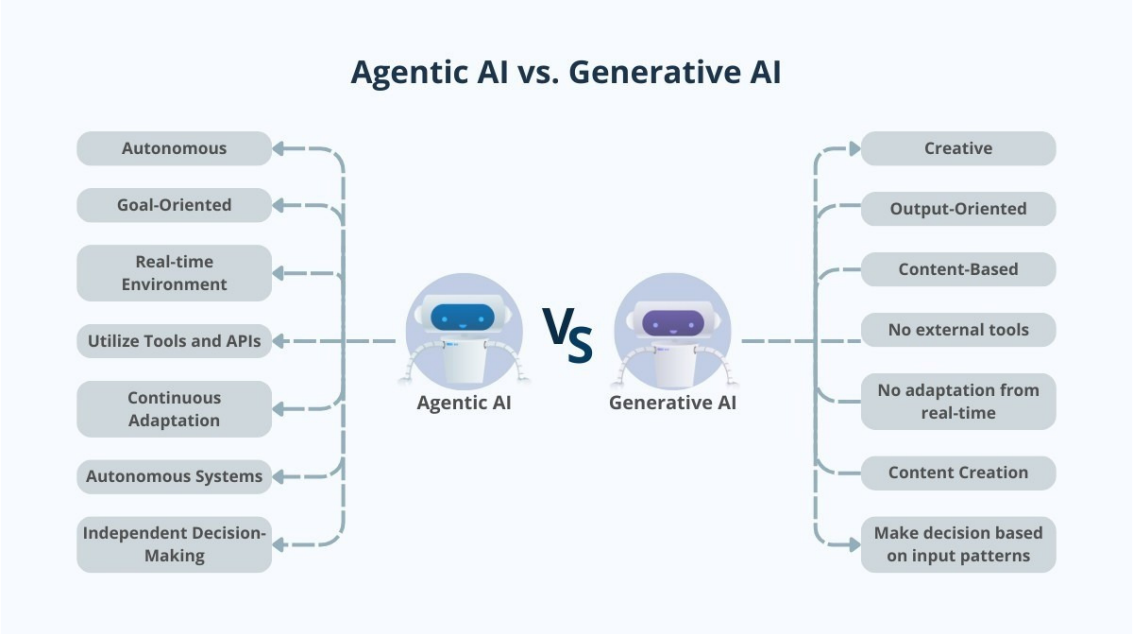
Agentic Artificial Intelligence refers to advanced AI systems capable of autonomous decision-making. These systems not only perceive and analyze their environment, but also set goals, plan actions, execute tasks, and adapt based on feedback with minimal human intervention (Craig, 2024; Microsoft via UC, 2025).

What is an Agentic AI Robo-Advisor?

In finance, Agentic AI powers a new generation of robo-advisory. Unlike conventional robo-advisory that strictly follow predefined rules, agentic robo-advisory act autonomously, dynamically interpreting market data, adjusting strategies, executing trades, and refining decisions over time without constant human supervision (Kapron, 2025; WEF, 2024).

Your participation is completely voluntary, and there are no right or wrong answers. All responses will be kept confidential and used only for academic purposes. The survey will take approximately 10–15 minutes to complete.

Different between Agentic AI & Normal AI



Demographics

Age

- 18-21
- 22-24
- 25-28

Gender

- Male
- Female

State

- Johor
- Kedah
- Kelantan
- Melaka

- Negeri Sembilan
- Pahang
- Pulau Pinang
- Perak
- Perlis
- Selangor
- Terengganu
- Sabah
- Sarawak

Education Level

- Secondary school (SPM, O-Level, equivalent)
- Pre-university / Diploma / Foundation (STPM, A-Level, Matriculation, Polytechnic)
- Bachelor's degree
- Master's degree

Monthly income range

- Less than RM2,000
- RM2,000 – RM3,999
- RM4,000 – RM5,999
- RM6,000 – RM7,999
- RM8,000 – RM9,999
- RM10,000 and above

How many years o investment experience do you have?

- No experience
- Less than 1 year
- 1–3 years

- 4–6 years
- more than 6 years

Have you used a robo-advisor be□ore?

- Yes
- No

Level o□Agentic AI understanding

- None
- Basic
- Intermediate
- Advanced

Perception o□Agentic AI robo-advisor replacing human advisor

- Positive
- Neutral
- Negative

Section 2: Risk Tolerance

This section aims to understand your personal attitude toward financial risk.

How would you describe your attitude toward risk-taking?

a. A real gambler

b. Willing to take risks after careful research

c. Cautious

d. Avoids risk at all costs

You're on a TV game show—choose one:

a. Take RM1,000 cash

b. 50% chance at RM5,000

c. 25% chance at RM10,000

d. 5% chance at RM100,000

You saved for a big vacation but lose your job three weeks before departure—you would:

a. Cancel the vacation

b. Switch to a more affordable trip

c. Go as planned, needing the break

d. Since you have no job at the moment, extend your vacation

If you received RM20,000 unexpectedly, you would likely:

a. Deposit in a safe bank or Certificate of Deposit (CD)

b. Invest in high-quality bonds or bond funds

c. Put in stocks or stocks mutual funds

How comfortable are you investing in stock or stock mutual funds?

a. Not comfortable at all

b. Somewhat comfortable

c. Very comfortable

What is word ‘risk’?

a. Loss

b. Uncertainty

c. Opportunity

d. Thrill

If most of your assets are in safe government bonds and experts predict bond prices to fall while hard assets may rise, you’d:

a. Hold onto the bonds

b. Sell half into money market, half into real assets (gold, properties)

c. Sell all bonds and buy real assets (gold, properties)

d. Sell all bonds, buy real assets (gold, properties), and borrow more to buy even more

Which investment do you prefer based on risk/return possibilities?

a. Best: +RM200, Worst: RM0

b. Best: +RM800, Worst: - RM200

c. Best: +RM2,600, Worst: - RM800

d. Best: +RM4,800, Worst: - RM2,400

If given RM1,000 in addition to what you own, you'd choose between:

a. Guaranteed gain of RM500

b. 50% chance to win RM1,000 and 50% chance for nothing

If given RM2,000 in addition to what you own, you'd choose between:

a. Guaranteed loss of RM500

b. 50% chance to lose RM1,000, 50% chance to lose nothing

An inheritance of RM100,000 is left to you, with instructions to invest it all. You'd pick:

a. Savings account or money market fund

b. Balanced stock & bond mutual fund

c. A portfolio of 15 common stocks

d. Commodities like gold, silver, oil

If investing RM20,000, you'd allocate:

a. 60% low-risk, 30% medium-risk, 10% high-risk

b. 30% low-risk, 40% medium-risk, 30% high-risk

c. 10% low-risk, 40% medium-risk, 50% high-risk

A friend invites you to an exploratory gold-mine venture with a 20% success chance but a payoff of 50–100x your investment if successful. You'd put:

a. Nothing

b. One month's salary

c. Three months' salary

d. Six months' salary

Section 3

For each statement, please indicate how much you agree or disagree:

1 = Strongly Disagree, 5 = Strongly Agree

Perceived Pleasure (PP)

PP1: I think I would enjoy using the Agentic AI robo-advisor.

PP2: Interacting with the Agentic AI robo-advisor is likely to feel pleasant.

PP3: The Agentic AI robo-advisor would make investing feel more fun and engaging.

Anthropomorphism (AN)

AN1: The Agentic AI robo-advisor communicates like a human.

AN2: The Agentic AI robo-advisor behaves in a human-like way.

AN3 : The Agentic AI robo-advisor seems to think or reason like a human.

Functionality (FT)

FT1: The Agentic AI robo-advisor would help me to generate better investment return.

FT2: The Agentic AI robo-advisor offers useful investment tools and features.

FT3: The Agentic AI robo-advisor helps me save time by automatically managing my investments and providing instant reports.

In□ormation (IF)

IF1: The Agentic AI robo-advisor provides clear explanations for its recommendations.

IF2: The Agentic AI robo-advisor gives enough details for me to understand why it made a recommendation.

IF3: The information from the Agentic AI robo-advisor is easy to understand.

Perceived Knowledge (PK)

PK1: I feel I understand how Agentic AI robo-advisors work.

PK2 : I believe I have enough knowledge about Agentic AI robo-advisors to use them confidently.

PK3 : I am familiar with what Agentic AI robo-advisors can and cannot do.

Perceived Benefit (PB)

PB1 : Using the Agentic AI robo-advisor would help me make better-informed investment decisions.

PB2: The Agentic AI robo-advisor would provide personalised recommendations that fit my goals.

PB3: The Agentic AI robo-advisor makes daily financial management easier by reducing costs and saving time.

Affective Trust (AT)

AT1: I would feel comfortable letting the Agentic AI robo-advisor handle my investment needs.

AT2 : I would feel at ease sharing my personal investment information with the Agentic AI robo-advisor.

AT3: I feel secure relying on the Agentic AI robo-advisor for important financial decisions.

Cognitive Trust (CT)

CT1: I believe the Agentic AI robo-advisor is competent in making investment decisions.

CT2: I believe the Agentic AI robo-advisor gives reliable and accurate recommendations.

CT3: I believe the Agentic AI robo-advisor will act in a consistent and dependable way.

User Acceptance (UA)

UA1: I intend to try an Agentic AI robo-advisor in the future.

UA2: I would recommend an Agentic AI robo-advisor to friends or family.

UA3: I am willing to rely on an Agentic AI robo-advisor regularly.

Section 4: THANK YOU!

Your honest opinions are highly valuable in helping us better understand how Malaysians view the future of AI in finance.

Thank you very much for your time and contribution.