Doctoral School of Economics, Business, and Informatics

Understanding User and Investor Perspectives on Robo-Advisors Adoption in Fintech

Ph.D. Dissertation in Business Informatics

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List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
AVE	Average Variance Extracted
BI	Business Intelligence
CC	Cognitive chatbots
COG	Cognitive Model
DOI	The Diffusion of Innovations
ECM	Information Systems Expectation Confirmation Model
EE	Effort Expectancy
FC	Facilitating Conditions
GDPR	General Data Protection Regulation
HM	Hedonic Motivation
HET	Humanizing Experience Theory
HA	Habit
HTMT	Monotrait ratio of correlation
IS	Information Systems
ML	Machine Learning
MM	Motivational Model
NLP	Natural language processing
PE	Performance Expectancy
PIQ	Perceived Information Quality
PLS	Partial Least Squares
PR	Perceived Risk
PSEQ	Perceived Service Quality
PSYQ	Perceived System Quality
PU	Perceived Usefulness
PV	Perceived Value
RA	Robo-advisors
SCT	Social Contract Theory
SEM	Structural Equation Modeling
SI	Social Influence

SJR	Scimago Journal Rank
SLR	Systematic Literature Review
SOR	Stimulus-Organism-Response
SRMR	Standardized Root Mean Square Residual
SRT	Social Response Theory
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
TTT	Trust Transfer Theory
USE	Use Behavior
UTAUT	The Unified Theory of Acceptance and Use of Technology

1. Introduction

Robots and artificial intelligence (AI) are revolutionizing various industries, including manufacturing, retail, and service. Even though automated technology penetration is increasing at a 20% annual pace, it is projected that roughly half of all present occupations will be replaced during the next two decades (Acemoglu & Restrepo, 2020; Belanche et al., 2019a; Huang & Lee, 2022a).

In the financial industry, financial technology (Fintech) has evolved into a significant component of bank and start-up business strategies (Elia et al., 2023). Fintech is more than consumer e-banking and digitalization; it entails creating and effectively deploying innovative financial technology solutions that address consumers' requirements and aspirations. As a result, AI has the potential to significantly expedite the financial industry's transition by enhancing customer value and company profitability (Park et al., 2016). Over one million Bank of America clients rely on the "Erica" chatbot for simple financial inquiries (Srivastava, 2021). In Bank of Tokyo branches, Nao, a little humanoid bank teller, works alongside real-life bank personnel (Marinova et al., 2017). So far, one of the key Fintech innovations has been robotic or artificial intelligence-assisted investment management, often referred to as “Chatbots-advisors/ Fintech Chatbots/AI-Chatbots/ Robo-advisors”.

Robo-advisors are automated, algorithm-driven financial advisory platforms that provide investment management services with minimal human intervention. These digital platforms use artificial intelligence (AI), machine learning (ML), and big data analytics to assess clients’ financial situations, risk tolerance, and goals and generate personalized investment portfolios. Robo-advisors democratize wealth management by offering low-cost, scalable, and data-driven investment solutions to both retail and institutional investors (Brenner & Meyll, 2020; Hong et al., 2023; Sabir et al., 2023; Wexler & Oberlander, 2021; Wu & Gao, 2021; Yeh et al., 2023; Zhu et al., 2023b).

Robo-advisers are a viable alternative to traditional human financial advisors, who charge more fees and can have limited office hours (Faubion, 2016; Park et al., 2016) . As a result, self-driving technology is anticipated to increase the accessibility of financial adviser services to a broader customer base (Sironi, 2016). As a result of their establishment, banks and other financial institutions use Robo-advisors (RA) as a source of competitive advantage. RA is increasing at over 30% each year, managing over $880 million in assets, and the Robo-advisors segment, asset under management assets are projected to reach US$1.78tn in 2022 (Statista, 2022; Waliszewski & Warchlewska, 2020).

Even though consumers have been "reluctant to accept" Robo-advisor services (Brüggen et al., 2024), some early users were cautious about placing their trust in this new system, which is shifting long-established financial management practices (Laukkanen & Pasanen, 2008). Following a few users' first adoption of the service, groups have been striving to expand their reach to a larger population that may be suspicious of the value of such an invention (Gallo et al., 2024). Managers want direction on integrating RA efficiently to retain and attract new consumers.

Despite the potential benefits of Fintech AI applications, research on using Robo-advisors is still relatively scarce. Most studies on this issue have paid scant attention to the customer's perspective (Arnone, 2024; Huang & Lee, 2022b), even though this would aid in distributing these services. Given the paucity of study in this area, academics have underlined the need to improve the usability of Robo-advisor systems (Alabbas & Alomar, 2025). With so many people interested in the potential benefits of automated financial planning, a comprehensive model is necessary to understand better the main beliefs and motives that drive the widespread adoption of Robo-advisors.

Additionally, there is a need for some critical moderating elements to ensure the acceptability of these sorts of AI-driven advances. Some people have previously encountered AI and robot-based systems via services like Alexa and devices like Roomba. The study's methodology suggests that familiarity with AI and robot-based systems may have a moderating effect. Consumers more familiar with robots may place a higher premium on their attitudes and judgments of their utility. In contrast, those less familiar with robots may select based on subjective factors. Few earlier studies on technology use focused on age and gender as control variables (Sun & Zhang, 2006). To summarize, organizations seeking to flourish in adopting Robo-advisors must understand their client's requirements and desires.

It is necessary to fill a gap in the existing literature and investigate and determine the significance of key factors (specifically utilitarian and social motivations) in a customer's decision to use a robot advisor system. If the investigation also considers customer characteristics such as culture, age, familiarity with robots, and gender and assesses potential variations in the adoption process, results can be comprehensive. Furthermore, it will explore how these characteristics may impact the relationships within this framework. To properly guide AI-powered innovation, it is crucial to comprehend and examine customer perceptions about Robo-advisor services and their prospective advantages for organizations and the general public.

Various instant mobile messaging services have evolved, and users may communicate with AI assistants using text-based interfaces, including Facebook Messenger, WhatsApp, Skype, Slack, WeChat, and Telegram (Guise, 2024). Moqaddamerad and Tapinos (2023) argue that the proliferation of instant messaging applications signals a sea change in the dynamics of the customer-business relationship and presents new possibilities for effective service delivery. Online financial firms like PayPal, Square, Robinhood, and traditional banks like JPMorgan Chase, Wells Fargo, and HSBC have adopted fintech Robo-advisors to provide quicker and more convenient solutions to customer inquiries. These financial Robo-advisors (also known as "virtual financial assistants" or "finbots") assist users at every stage of their financial journey—from account management and transactions to real-time support during financial decisions and investments and even post-transaction assistance with customer service needs (Cit et al., 2025).

Though conversational interfaces first surfaced on smartphones, they have now been adapted to a wide range of other smart devices, such as social robots for customer service and speech platforms like Siri, Cortana, and Alexa from Apple, Microsoft, and Amazon, respectively (McTear et al., 2016). Because they can understand and translate speech into action, these voice platforms may be seen as the next step in developing Robo-advisors (Suhaili et al., 2021). Rather than serving as a marketing tool, they are made to help people with a variety of everyday activities, including finding nearby restaurants or motels, checking the weather, finding their way to work, playing music, setting alarms, and managing other smart home appliances (e.g., lights). Kayak's digital voice assistant, which has been released on key voice platforms, including Amazon Alexa and Google Assistant, is one example of the application of speech platforms in the travel and tourism industry. KLM's "Blue Bot" (BB) on Google Assistant is an AI service bot that helps passengers with bookings and packing suggestions based on their destination, freeing them up to concentrate on trip itinerary rather than details (Ling et al., 2023).

Companies are increasingly using conversational agents to improve customer support quality, productivity, and efficiency, but the results have been mixed (Marikyan et al., 2022).

Significant obstacles exist for the conversational user interfaces of existing AI Assistant apps, such as the AI Assistants' frequent failures to capture diverse open-ended inquiries (Liang et al., 2024). So far, AI assistants are not always capable of deciphering users' speech in its entirety, and they also struggle with more complex dialogues. In addition, many customers are still hesitant to use AI assistants, preferring to communicate with live operators. Understanding what makes for a pleasant discussion is crucial to creating helpful Fintech aids. It also looks at ways to improve the user experience of AI assistants to increase their uptake. Therefore, this study aims to investigate the main elements that influence people's decision to employ AI assistants while evolving to Fintech.

A new research agenda is centered on AI, mainly Robo-advisors, as an assistant in the service industries (such as marketing, business, finance, tourism, and hospitality). Thus, this study has several theoretical and practical implications. Although there is a growing body of research on AI's social implications, there is a shortage of literature on how and whether AI assistants will be used in Fintech organizations. In particular, no studies have looked at users' behavior intentions and satisfaction with the process and consequences of interacting with AI Assistants in Fintech. This research helps close a knowledge gap in the field by illuminating the factors that contribute to user satisfaction and the connection between that satisfaction and plans to use AI assistants while on the road. Among the Fintech literature, this study is one of the first to scientifically analyze users' attitudes toward AI Assistant systems, including their interest in adopting and using them. This research fills a void in the literature by developing and validating scales of factors influencing user satisfaction and behavioral intentions of AI Assistants for Fintech, which will add depth to the application of consumer behavioral theories to the field of artificial intelligence (AI) assistants.

The results have real-world implications for better developing, expanding functionality, and utilizing AI Fintech assistants. Therefore, understanding what motivates or discourages customers from using fintech Robo-advisors is valuable for both Robo-advisors developers and financial service providers, such as banks and fintech firms. This knowledge helps them meet customer demands and enhance their overall experience with digital financial services. This thesis will thus make a valuable contribution by providing guidelines for better customer service and a more satisfying customer experience. *Due to human involvement and the financial sector's involvement, privacy, security, and trust play key roles in research on robo-advisors. Thus, this research aims to analyze Robo-advisors users'/investors' perspectives on and acceptance of Robo-advisors. The current research explores issues such as trust, security,* *and privacy in robo-advisors used in the financial sector and user beliefs that may influence adoption. There are two levels of problem statements, level 1 (Kasilingam, 2020; Murtarelli et al., 2021) and level 2 (Rese et al., 2020) (Aslam et al., 2022) (Araújo & Casais, 2020), identified: Level 1: There is a need to address the problem of financial services customers regarding trust, security, and privacy. Level 2: Financial services users are less accepting of Robo-advisors and less likely to employ them.*

The thesis aims to determine factors influencing people's attitudes about and future use of artificial intelligence-based (AI) Fintech assistants. The overarching goal is to show how consumers rate the quality of their Fintech-related interactions with AI assistants/ Robo Advisors. Following is the research objective in the context of the above two prescribed problems,

- Firstly, to analyze how Robo-advisors address the issues of trust, security, and privacy of data for investor/ Robo-advisors' users.
- Secondly, to investigate the factors significant to the perceived competence of Robo-advisors for acceptance and usage by investors/ Robo-advisors' users.

The first chapter of the thesis will illustrate the introduction and elaborate on the topic's importance. The second chapter will present a literature review, The third chapter will provide an overview of the research, and the fourth chapter will discuss the methodology adopted for the thesis. The fifth chapter will deliver the results regarding interview analysis, as firstly, interviews conducted with Fintech leaders and staff will illustrate the challenges and opportunities for Robo-advisors in Fintech. The sixth chapter will describe the systematic literature reviews and the theories and methods used to understand the Robo-advisors' role in Fintech. The seventh chapter will discuss the research from models applied to uncover the determinants for the acceptance of AI-chatbots/Robo advisors, and the eighth chapter will provide an absolute discussion of the conclusion on future direction.

2. Literature Review

This chapter begins with a brief history of artificial intelligence and an overview of its current state of development. It then explores the practical applications of AI across various sectors. The discussion shifts to the relationship between humans and AI assistants, addressing key challenges such as natural language comprehension, user resistance and trust, privacy concerns, and safety risks. In the final section of the chapter, we examine the theoretical foundations of why and how people will accept AI technology. This chapter summarizes ideas on adopting and accepting technology pertinent to the thesis's suggested research framework.

Artificial Intelligence (AI) has become an integral part of the business world, transforming how businesses operate and interact with customers (Ritala et al., 2023; Wang et al., 2022). In recent years, the development of Robo-advisors has garnered significant attention as an application of artificial intelligence (Lund et al., 2023). Robo-advisors are computer programs designed to simulate human conversation and can be used for customer service, consumer engagement, and streamlining business operations (Xie et al., 2023). This literature review will examine the use of AI-based chatbots in the context of business and analyze the benefits, challenges, and future implications of this technology.

AI-powered chatbots offer numerous benefits to enterprises (de Andrés-Sánchez & Gené-Albesa, 2023a). Cost reduction is one of the primary advantages(Fotheringham & Wiles, 2022; Zheng et al., 2023). Robo-advisors are capable of performing routine customer service duties, such as responding to frequently asked inquiries, without requiring human intervention. It saves businesses time and money by reducing customer service representatives' workload. Additionally, Robo-advisors can operate 24 hours a day, seven days a week, providing immediate support to customers, which can increase customer satisfaction and retention. Another advantage of AI-powered chatbots is their capacity to acquire and analyze customer data. Robo-advisors can collect data on consumer preferences, behavior, and requirements, which can be used to enhance business operations, marketing strategies, and product development. This data can also personalize the customer experience, increasing customer satisfaction and brand loyalty. By automating tasks such as appointment scheduling, order monitoring, and payment processing, chatbots powered by AI can also improve operational efficiency. It reduces the workload of human employees and frees them up to concentrate on duties that require human intelligence but are more complex (Nirala et al., 2022).

2.1. History and Origin of AI

Artificial Intelligence (AI) has become integral to various industries, including corporate decision-making, healthcare, weather forecasting, and more. Its widespread application is transforming business processes, jobs, and sectors. AI's development began with early concepts of intelligence, leading to innovations like mechanical calculators in the 1600s, the first neural network models in 1943, and the coining of "Artificial Intelligence" by John McCarthy in 1956. The evolution of AI has seen significant milestones, such as IBM's Deep Blue defeating the world chess champion in 1997, the emergence of deep learning in 2006, and the groundbreaking success of AI applications like Google Brain and Open AI. AI can be categorized into two main types based on capacity and functionality. Capacity-based AI includes Narrow AI, which performs specific tasks autonomously, and General AI, which can mimic human intelligence across diverse tasks. Super AI, though theoretical, could surpass human intellect in processing and judgment. Functionality-based AI ranges from reactive machines to limited memory systems, with future advancements aiming for AI capable of understanding emotions and becoming self-aware. While only Narrow AI is currently in use, these developments signal AI's transformative potential, though concerns about its future capabilities and implications remain prevalent (Abbas et al., 2023; Horvath & Symonds, 1991; Pramod Kumar et al., 2021; Sreenivasan & Suresh, 2024; Williamson & Eynon, 2020).

Until now, only Narrow AI or Limited Memory has been identified. To further comprehend and expound on the future of AI in finance, this research will concentrate on a subtype of these AIs called Robo-advisors.

2.1.Robo-advisors overview

As technology progresses, there will always be a requirement for intelligent agents. The fundamental objective of Robo-advisors was to assist clients by responding to their inquiries. Due to the potential for businesses to employ this technology, Robo-advisors are attracting massive attention on the internet today. They are often used across many sectors since they provide the best possible connection between a business and its clients. The cornerstone of Robo-advisors is natural language processing (NLP). NLP is the technology that comprehends spoken language in the same way as Google Now, Apple Siri, and Microsoft Cortana do. The figure below illustrates how NLP works. After receiving data in any format (textual or voice), a Robo-advisor can recognize the complex algorithms in each message the user gives (Nirala et al., 2022). The user defines what they plan to say and how they wish to be responded to in this message.

Intelligent agents (Injadat et al., 2021) are novel software that holds significant potential for many internet applications. When they were initially introduced, they served as intelligent interfaces, personal assistants, and a way for intelligently processing mail, client inquiries, and more. As time passed, Robo-advisors transformed the e-commerce industry and were eventually included in every e-commerce platform. The firm's customer-to-customer (C2C) and business-to-business (B2B) segments were also harmed. It was a revolution, as their position required them to answer customers' issues around the clock, even outside of the company's typical business hours. There was no limit to the number of queries or response times. Robo-advisors have a wide range of applications in several industries, including banking, marketing, healthcare, language translation, travel, real estate, and fashion (Ahmad et al., 2024). Numerous services, including Facebook Messenger, Viber, WhatsApp, and Slack, are compatible.

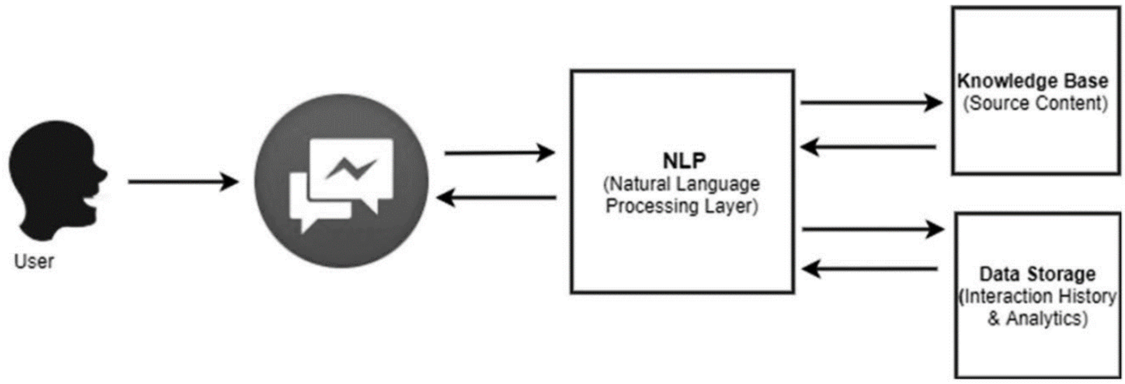

Figure 1: Natural Language Processing Process

(Pramod Kumar et al., 2021)

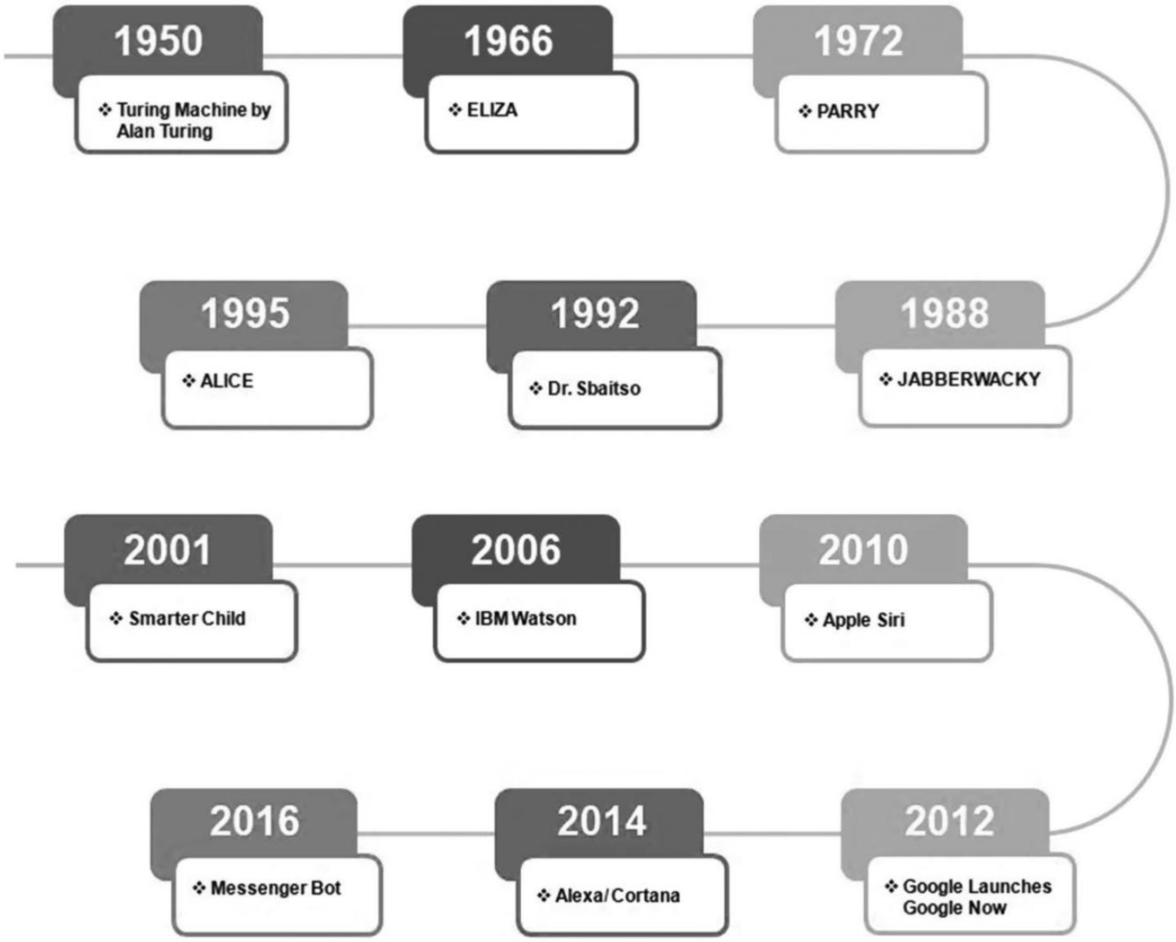

Figure 2: Evolution of Robo-advisors source(Pramod Kumar et al., 2021)

By 2015, Telegram and Slack had opened their bot systems to outside developers and businesses interested in creating Robo-advisors to provide their consumers with a wide range of services (i.e., communication for customer service). In April 2016, Facebook introduced chatbots to its Messenger platform; being a significant participant in the chatbot platform industry, Facebook is often credited with having had a considerable effect on the growth of chatbots (Zhou & Chang, 2024). Because of the proliferation of instant messaging, the traditional communication methods between companies and their clients have undergone significant changes. The commercial potential of chatbot technology for improved customer service and digital marketing is increasingly being recognized by major corporations. Rather than developing native mobile apps, Joshi et al. (2025) forecast that businesses will focus on developing chatbots.

As processing power has increased, it has been possible to make new technological improvements in response to challenging working world requirements. Technological enhancements would have been impossible without artificial intelligence (AI). Natural language processing (NLP) is a critical application of artificial intelligence. Natural language processing, sometimes referred to as NLP, is one of the most crucial applications of artificial intelligence. Natural Language Processing (Teller, 2000) teaches a machine or computer to interpret and decode human speech. Teller conceived of this approach. Conversational AI bots, commonly referred to as Chatbot Systems or bots that engage in conversations with humans, are an integral component of natural language processing. These bots are sometimes referred to as Conversational AI Bots.

AI Chatbots is replacing human responses because they are more accurate and genuine. In recent years, artificial intelligence development, machine learning, and other underlying technologies, such as neural networks and NLP, have increased the usage of chatbots, also known as virtual assistants, as conversational interpreters between people and bots. These developments have enabled chatbots to simulate human communication patterns. These chatbots can connect with any human being efficiently by utilizing interactive inquiries. Numerous cloud-based chatbot services, such as IBM Watson, Clever Bot, and ELIZA chatbot, have lately increased their availability to develop and advance the chatbot sector (Benaddi et al., 2024). The art of human-robot interaction has evolved tremendously over the last several years as these conversational agents have become more responsive.

2.3. Types of Robo-advisors

Even in highly sophisticated domains, manual labor led to the arrival of the modern period of the present technology. This recent progression has benefited industries such as customer service through the development of Robo-advisors.

Madhuridevi and Sree Rathna Lakshmi (2025) identify several distinct Robo-advisors varieties, such as flow-oriented, artificially intelligent, or hybrid. In contrast to free-form text entry, the decision-tree-based approach of flow-oriented Robo-advisors (also called rule-based Robo-advisors) makes extensive use of buttons and keywords. The user is guided down a predetermined path set by the Robo-advisors creator; the user is given free will to make choices within the bounds of the path but cannot deviate from it (Wester et al., 2024). While useful for simple inquiries, these bots aren't the best option for services that need more complex situations with various variables and components because of their poor response times and inability to guide customers to their intended goals. In addition, Robo-advisors with AI capabilities may process data and reply conversationally by leveraging natural language processing and machine learning technology. When combined with machine learning techniques, AI-enabled chatbots

(Robo-advisors) can compute and learn from user inputs, comprehend user intents, and produce the best correct response possible. Hybrid Robo-advisors, which combine a flow-oriented button selection system with a natural language mechanism, are now the most often used type of Robo-advisors (Wester et al., 2024). This type of Robo-advisors can direct the user down a predetermined path. Still, it can also accommodate free text and interactions as needed, such as the demands of entirely unrelated users at any time (Puerta-Beldarrain et al., 2024). The most popular platform-independent UI components, according to (Yu et al., 2024), are the carousel (with image, title, subtitle, and buttons), the rapid reply (with title, text, picture), and the button (including title, payload text or URL). By contrast, not all Robo-advisors are created equal. They are divided into categories based on their usability and computational complexity.

2.3.1. Menu/Button-Based Robo-advisors

Menu-based Robo-advisors, such as buttons and top-down menus, are the most prevalent and straightforward Robo-advisors available today. You will be taken through a decision-making process similar to a decision tree while interacting with these Robo-advisors. The user is educated to make these decisions by selecting options and delving deeper to get the appropriate answer from artificial intelligence. These menu-based Robo-advisors answer slowly and cannot be depended upon to offer to solve issues or the information you want (Gupta et al., 2020; Thakkar et al., 2021).

2.3.2. Keyword Recognition-Based Robo-advisors

These Robo-advisors are trained to recognize specific phrases to accomplish the desired goal. User input is analyzed, and suitable action is performed. The bot provides an appropriate response to the user using algorithms and a customized keyword list. A Robo-advisor performance degrades when the exact words appear in many related searches. A user may inquire, "How do I configure auto-login authentication on my phone?" and the bot will use keywords such as "auto" and "login" to find the most relevant response (Gupta et al., 2020; Thakkar et al., 2021).

2.3.3. Contextual Robo-advisors

They are one of the most technologically sophisticated Robo-advisors accessible today. They employ artificial intelligence and machine learning technology to understand the user's emotions, including speech recognition and speech-to-text conversion algorithms. The fundamental principle of this type of bot is to ascertain the user's aims and then deliver an intelligent answer based on knowledge of the database's pattern of activity. Over time, when the bot experiences a broader variety of scenarios, it will learn and improve. Consider a dinner delivery app as a simple example. The user's payment method, delivery address, and previous orders are stored in the database here. For instance, a Robo-advisor can ascertain a user's perspective and recommend things based on prior purchases or interests (Gupta et al., 2020; Kandpal et al., 2020).

2.4 Business Context

Artificial Intelligence System (AIS) applications have expanded the technological frontiers in many sectors, including medicine, business, manufacturing, transportation, education, and government (Olan et al., 2024). Voice recognition, facial expression recognition, robot navigation, automation, data mining, knowledge representation, handwriting recognition, speech recognition, computer vision, virtual reality (VR), and image processing are just a few of the many AI applications that have widespread use. Google Duplex, an AI assistant, debuted in 2018 as one of the most cutting-edge forms of AI. Duplex can phone local businesses (such as hair salons and restaurants) and arrange appointments and bookings on behalf of consumers. It demonstrates how the intelligent assistant can aid with practical activities, such as making a dinner reservation, with just a few words spoken over the phone. Since it is still in its infancy, you can only use it at a small subset of eateries for now. The number of people who utilize this technology (consumers and service providers alike), the percentage of people who would rather interact with an AI than a human, and the likelihood that service providers would always accept AI-made reservations all factor towards the technology's ultimate success.

Liu et al. (2020) explored multiturn response triggers in customer care Robo-advisors to correct and mislead during the discussion process. Sarbabidya and Saha (2020) investigated the importance of online banking in ensuring the growth and development of a business's operations. Any industry where assistance may be delivered without human intervention would profit from adopting a Robo-advisor (Kasinathan et al., 2020). Prabu et al. (2020) suggest the usage of customer assistance Robo-advisors powered by artificial intelligence (AI) in customer service. Sheehan et al. (2020) observed that unsolved flaws are crucial for reaching the goal of widespread adoption of customer support Robo-advisors. Chung et al. (2020) observed that Robo-advisors' e-services provide clients with immersive and engaging customer support experiences. Trust can be influenced by the features of the Robo-advisors, which can be categorized as privacy, perceived security, and the Robo-advisors host’s brand. Additionally, similar to what Behera et al. (2024) reported, we discovered that Robo-advisors might be used to deliver personalized attention to consumers and improve relationships between users and businesses. Additionally, customer care chatbots can benefit consumers on social and economic levels and enhance brand performance (Behera et al., 2024). According to the logic of the above arguments, none of the literature on AI-chatbot-based customer service has examined concerns of personalization and context.

While AI-based chatbots offer numerous advantages to businesses (de Andrés-Sánchez & Gené-Albesa, 2023a), they also present several challenges that must be addressed. The development and maintenance of Robo-advisors is one of the primary obstacles. Developing a Robo-advisor capable of effective consumer communication requires significant resources and expertise. In addition, Robo-advisors must be continuously updated and maintained to ensure their continued effectiveness (Chow et al., 2023). Another difficulty is the possibility that Robo-advisors will provide incorrect or irrelevant responses to clients. It can harm the customer's perception of the company, diminishing customer satisfaction and loyalty (Hsu & Lin, 2023; Zhang et al., 2023). Robo-advisors must be trained to recognize and respond accurately and efficiently to consumer questions. Concerns regarding privacy and security are also associated with AI-based chatbots (Kooli, 2023). Customer data collected and stored by Robo-advisors can be used for marketing purposes or sold to third parties. It raises questions regarding the privacy and security of consumer data. Businesses must comply with privacy regulations and take the necessary precautions to safeguard consumer information. In the future, AI-powered chatbots in business are anticipated to increase significantly (Baabdullah et al., 2022; Gołąb-Andrzejak, 2023). The sophistication of Robo-advisors will improve with more advanced features such as voice recognition, sentiment analysis, and predictive analytics (Ahmed et al., 2022). It will allow chatbots to provide more effective and personalized consumer service. As chatbots become more widespread, businesses must modify their customer service strategies to effectively integrate them. It will necessitate training employees to work alongside Robo-advisors and ensuring that the transition between human and Robo-advisors' interactions is seamless for consumers. Using chatbots powered by AI also raises ethical and social concerns that must be addressed. The use of Robo-advisors may result in the loss of jobs for customer service representatives or traditional financial advisors, raising concerns about the obligation of businesses to retrain and reskill workers. Concerns exist regarding the potential for Robo-advisors to perpetuate biases and discrimination, underscoring the need for ethical considerations in developing and using Robo-advisors (Mohamed, 2023).

AI-powered chatbots offer numerous advantages to businesses, including cost savings, enhanced operational efficiency, and personalized customer service (Paul et al., 2023). However, many challenges and implications must be addressed, such as the creation and maintenance of messaging programs, the risk of providing inaccurate or irrelevant responses, and privacy and security concerns. As Robo-advisors become more widespread, businesses will need to adapt their customer service strategies, ensure they are in compliance with privacy regulations, and take the necessary precautions to safeguard customer data (Rivas & Zhao, 2023). The future implications of AI-powered chatbots (Robo-advisors) in the business context are substantial, as Robo-advisors are anticipated to become more sophisticated and offer advanced features. Nonetheless, ethical and social implications must be addressed, such as unemployment and the perpetuation of prejudice and discrimination.

Consequently, businesses and developers must consider the ethical implications of Robo-advisors and take the necessary steps to ensure that they are developed and utilized responsibly. Overall, Robo-advisors powered by AI have the potential to revolutionize how businesses operate and interact with consumers (Rivas & Zhao, 2023). While there are challenges and ramifications to consider, Robo-advisors offer significant benefits and a bright future for businesses seeking to streamline operations and increase customer satisfaction. As technology continues to advance, it will be crucial for companies to remain abreast of the most recent innovations and integrate Robo-advisors into their overall customer service strategy (Rizomyliotis et al., 2022).

In addition, as Robo-advisors become more pervasive, businesses will need to consider the impact on human employees and provide adequate training and support (Bavaresco et al., 2023; Haleem et al., 2022). It will assist employees in adapting to the evolving nature of customer service and enable them to collaborate effectively with Robo-advisors. Marketing represents a prospective development area for AI-based chatbots (Robo-advisors) in the business context (Rivas & Zhao, 2023). Customers' preferences, behaviors, and requirements can be gathered using Robo-advisors. This information can then be used to inform marketing strategies and provide customers with personalized promotions. As Robo-advisors advance, they will be able to offer increasingly sophisticated marketing assistance, such as sentiment analysis and predictive analytics (Ahmed et al., 2022). In addition to e-commerce, e-commerce is a potential growth sector for Robo-advisors. Robo-advisors can be used to assist consumers with the purchasing process by providing product recommendations and answering inquiries. It can increase sales, consumer satisfaction, and operational efficiency (Hsu & Lin, 2023). Robo-advisors have the potential to revolutionize how companies interact with consumers on social media. Robo-advisors can be used to respond in real-time to consumer questions and complaints, providing swift and efficient support. It can increase consumer satisfaction and assist companies in maintaining a positive reputation on social media platforms. AI-powered chatbots (Robo-advisors) provide businesses with significant cost savings, enhanced operational efficiency, and personalized customer service. However, there are challenges and implications that must be addressed, including development and maintenance, the accuracy and relevance of responses, and privacy and security concerns. As the prevalence of Robo-advisors increases, businesses will need to alter their customer service strategies and consider the technology's ethical and social implications. Despite this, the future of AI-powered chatbots in the business context is bright, with significant growth and transformation potential in various fields, including marketing, e-commerce, and social media engagement (M. S. Rahman et al., 2023).

Further research and development will be required to realize the maximum potential of AI-based chatbots in business (Dwivedi et al., 2023; Sarker, 2022). It includes advancements in natural language processing, sentiment analysis, and machine learning, which will allow chatbots to provide more personalized and effective customer service (El-Ansari & Beni-Hssane, 2023). In addition, it will be essential to resolve privacy and security concerns, ensure that businesses comply with regulations, and take the necessary precautions to safeguard consumer data. The use of chatbots in multilingual customer support is an additional area that could be investigated. As companies expand their global scope, they will be required to interact with customers who speak various languages. Chatbots could provide multilingual support, allowing businesses to communicate with consumers regardless of their language. AI-powered chatbots provide businesses with significant cost savings, enhanced operational efficiency, and personalized customer service (Fotheringham & Wiles, 2022). Even though there are challenges and ramifications to consider, the future of Robo-advisors in the business context is bright, with significant growth and transformation potential in areas such as marketing, e-commerce, and social media engagement. To realize the maximum potential of this technology and resolve concerns regarding privacy, security, and ethics, continued research and development in the field will be required. As businesses increase their use of Robo-advisors, they will need to modify their customer service strategies and evaluate the impact on human employees. Overall, the use of AI-powered Robo-advisors in the business context signifies a significant advancement in the evolution of consumer service and engagement (Le, 2023; M. S. Rahman et al., 2023).

Trust is a significant factor in adopting and succeeding AI-based Robo-advisors in the business context (Gkinko & Elbanna, 2022; Song & Shin, 2022). Trust is the extent to which consumers perceive Robo-advisors to be dependable, secure, and effective at providing customer service (Chen et al., 2023). Intentions are also to investigate the various factors that influence Robo-advisors' trust, such as privacy, perceived security, and Robo-advisors host brand (Dinh & Park, 2024). Privacy is one of the most influential factors in Robo-advisors' credibility (Bouhia et al., 2022). Customers must have faith that their personal data is being handled securely and that Robo-advisors are not accumulating superfluous information. According to research, customers are more likely to trust transparent Robo-advisors about their data collection practices and provide straightforward explanations of how the data will be utilized (So, 2021). Customers' trust can be bolstered by Robo-advisors that capture data only when necessary and provide customers with options to manage their data. Perceived security is another factor that influences Robo-advisors' credibility (Yen & Chiang, 2021). Customers must believe that Robo-advisors are secure and that their data is safe from hackers and malicious actors. (Hasal et al., 2021).

Additionally, Robo-advisors that provide straightforward information about their security measures and methods for customers to report security issues can boost consumer confidence in technology (Javaid et al., 2023). The Robo-advisor operator is also an essential factor that influences Robo-advisors' trust. Customers are more likely to trust Robo-advisors when they are associated with reputable brands with a history of providing dependable and effective customer service (Shahzad et al., 2024). For instance, consumers are more likely to trust a well-known technology company's Robo-advisors than a small startup. Companies can increase trust in Robo-advisors by associating them with their brand and ensuring that their messaging and brand values are reflected in the Robo-advisors. In addition to these factors, personalization and context play significant roles in establishing Robo-advisors' credibility. Customers are more likely to have faith in Robo-advisors who offer individualized assistance based on their specific requirements and preferences (Shumanov & Johnson, 2021). For instance, Robo-advisors that utilize previous customer interactions and purchase history to provide personalized recommendations can increase customer confidence.

Moreover, Robo-advisors that provide context-specific support, such as location-based recommendations or language-specific support, can boost consumer confidence in technology (Hang et al., 2024). To increase consumer confidence in Robo-advisors, businesses must prioritize privacy, perceived security, the Robo-advisors host's brand, personalization, and context. By creating Robo-advisors that are transparent, secure, and associated with reputable brands, businesses can increase customer trust and adoption of Robo-advisors as an efficient customer service tool (Ramki et al., 2024). In addition, Robo-advisors that offer personalized and context-sensitive support can boost consumer confidence in technology and enhance the overall customer experience. Therefore, when developing customer service strategies, businesses should consider the factors that influence trust in Robo-advisors to establish trust in this technology and increase customer loyalty (Shahzad et al., 2024).

Additionally, it is essential to note that trust in Robo-advisors is not static and can fluctuate over time. Based on their interactions with Robo-advisors, consumers' perceptions of the technology may alter over time (Meier et al., 2024). For instance, if a Robo-advisor provides inaccurate or irrelevant responses, consumers may lose faith in the technology. Conversely, if a Robo-advisor consistently provides personalized and effective support, consumers may gain trust in the technology over time (Behera et al., 2024).

Consequently, businesses must monitor and analyze consumer interactions with Robo-advisors to identify areas for development and increase confidence in the technology (Savastano et al., 2024). By accumulating and analyzing customer feedback and data, businesses can gain insights into customer preferences and requirements and use this knowledge to improve the Robo-advisors' performance and increase customer trust. The importance of human personnel in the customer service process cannot be overstated. While Robo-advisors can provide consumers with efficient and personalized support, there are circumstances where human intervention is required (Al-Shafei, 2024). Therefore, businesses should ensure that Robo-advisors are designed to allow for seamless transitions between human and Robo-advisors interactions. It can help develop customer trust in Robo-advisors by enabling them to communicate with a human representative when necessary. Trust is crucial to the success of AI-powered Robo-advisors in business settings. To establish trust in Robo-advisors and increase consumer confidence in the technology, businesses must prioritize privacy, perceived security, the host's brand, personalization, and context (Chakraborty et al., 2024). In addition, businesses should monitor and analyze customer interactions with Robo-advisors to identify areas for refinement and ensure that Robo-advisors are designed to allow for seamless transitions between human and Robo-advisors interactions. As Robo-advisors develop and become more sophisticated, establishing confidence in this technology will be crucial for fostering customer loyalty and enhancing the overall customer experience (Singh & Singh, 2024).

Security is one of the most important factors influencing the adoption and success of AI-based Robo-advisors in business (Pillai et al., 2024). Robo-advisors that manage sensitive data such as personal information, payment information, and confidential business data must be designed with security in mind to prevent data breaches and intrusions. This literature review will examine the impact of authentication, encryption, and data protection on Robo-advisors' security (Jalali & Hongsong, 2024). Authentication is crucial to Robo-advisors' security because only authorized users can access it and its data. Various authentication methods are available, such as password-based, two-factor, and biometric authentication. The most prevalent authentication method for Robo-advisors is password-based but also the least secure (Kim & Lee, 2024). Two-factor authentication increases security by requiring a second identifier, such as a security token or biometric data. Biometric authentication, such as facial recognition or fingerprint detection, is the most secure authentication method, but additional hardware may be required. Encryption is another crucial aspect of Robo-advisors' security. Encryption safeguards and protects Robo-advisors' data from hackers and other malevolent actors (Bhardwaj, Dhaliwal, et al., 2024). The encryption methods available to Robo-advisor developers include symmetric encryption and asymmetric encryption. Asymmetric encryption uses a public key to encrypt data and a private key to decrypt it, whereas symmetric encryption uses a shared key to encrypt and decrypt data. Developers of Robo-advisors should employ encryption at all stages of the Robo-advisors operation, from data storage to data transmission. Data protection is another crucial aspect of Robo-advisors' security. Robo-advisors that manage sensitive information must be designed to prevent data breaches and intrusions with data security in mind (Dewitte, 2024). Robo-advisor developers can implement data protection in several ways, including data minimization, access controls, and routine data backups. Data minimization entails collecting and storing the least sensitive consumer information possible. Access controls restrict sensitive data and limit the number of users who can access Robo-advisors' data. Regular data backups ensure data recovery in the event of a data breach or cyberattack (Edwards, 2024).

Companies should also consider the ethical and legal implications of Robo-advisors' security in addition to these factors (Dewitte, 2024). Robo-advisors who handle sensitive information must comply with the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) (Awwal-Bolanta & Anakanire, 2025). Developers of Robo-advisors must also consider the ethical implications of Robo-advisors security, such as the perpetuation of prejudice and discrimination. Security is crucial to the success of AI-based

Robo-advisors in business settings. Developers of Robo-advisors must prioritize authentication, encryption, and data protection to ensure the security of Robo-advisors and the preservation of consumer data against cyberattacks and data breaches (Costa & Coelho, 2024).

Additionally, businesses should consider Robo-advisors security's moral and legal implications and adhere to privacy regulations. By designing Robo-advisors with security in mind and ensuring they comply with privacy regulations, businesses can develop customer trust and increase the adoption of Robo-advisors as an efficient customer support tool. In addition, Robo-advisors who prioritize security can assist companies in maintaining a positive reputation and avoiding expensive data breaches and legal repercussions (Li, 2023).

Additionally, it is essential to note that Robo-advisors' security is not static and requires continuous monitoring and updates to remain secure (Yang et al., 2023). As hackers and other malicious actors develop new techniques to compromise Robo-advisors' security, Robo-advisors' developers must stay current on the most recent security measures and alter their strategies accordingly. Regular security audits and revisions can assist in identifying vulnerabilities and enhancing the security of Robo-advisors. The potential for Robo-advisors to be used in phishing attacks or other malevolent activities is a further security concern. Using Robo-advisors, hackers can collect sensitive consumer information or distribute malware. Therefore, businesses must implement anti-phishing measures and malware detection software to prevent such attacks (Gallo et al., 2021).

Finally, it is important to note that Robo-advisors are not immune to human error (Burnette et al., 2024). Human employees who administer Robo-advisors may make errors that compromise security, such as leaving passwords or other sensitive data unprotected. Therefore, businesses must ensure that their employees are trained in Robo-advisors security best practices and know the dangers of Robo-advisors. Security is crucial to the success of AI-based chatbots in the business context. Developers of Robo-advisors must prioritize authentication, encryption, and data protection to ensure the security of Robo-advisors and the preservation of consumer data against cyberattacks and data breaches (Bokolo & Daramola, 2024). In addition, businesses must consider Robo-advisors' security's moral and legal implications and adhere to privacy regulations. Regular security audits and updates can help identify vulnerabilities and strengthen Robo-advisors' security, while anti-phishing measures and malware detection software can prevent malicious attacks. Businesses can develop consumer trust by prioritizing Robo-advisors' security and preserving their positive reputation in the market (Chakraborty et al., 2024).

Data privacy is an additional crucial factor influencing the adoption and success of AI-based Robo-advisors in business (Pillai et al., 2024). To protect consumer data from misuse and data breaches, Robo-advisors that manage sensitive data such as personal information, payment information, and confidential business data must be designed with data privacy in mind. The collecting of data is a crucial aspect of Robo-advisors' data privacy. Robo-advisors that collect customer data must be transparent about their data collection practices and obtain the customers' consent before collecting and using their data. Additionally, Robo-advisors should only acquire the necessary data to provide adequate customer service and retain as little sensitive information as possible. To further safeguard customer privacy, Robo-advisor developers should also consider anonymizing or pseudonymizing customer data (Hasal et al., 2021).

Data storage is another crucial factor that affects Robo-advisors' data privacy (May & Denecke, 2022). Robo-advisors storing client information must defend the data from hackers and malicious actors. Robo-advisor developers can implement security measures such as encryption and access controls to safeguard consumer data. To reduce the risk of data breaches and cyberattacks, Robo-advisor developers should also conduct routine audits of their data storage systems and erase superfluous data (Bhardwaj, Khan, et al., 2024). In Robo-advisors, data sharing is also a crucial factor that affects data privacy. Robo-advisors that share customer information with third parties must ensure that the data is used for legitimate purposes and that customer privacy is protected. Robo-advisor developers should only share data with third-party organizations with transparent privacy policies and adhere to privacy regulations such as GDPR and CCPA(Fernandez, 2023).

Companies should also consider the ethical and legal implications of Robo-advisors' data privacy in addition to these factors (Dewitte, 2024). Robo-advisors who manage sensitive data must adhere to multiple privacy regulations, such as GDPR and CCPA, and ensure that customer data is used ethically and with customer consent. Developers of Robo-advisors should also consider the possibility of discrimination and bias in Robo-advisors data and take measures to mitigate these risks (Kooli, 2023). Data privacy is crucial to the success of AI-based Robo-advisors in business settings. Robo-advisor developers must prioritize data collection, storage, and sharing to guarantee that customer data is used ethically and with customer permission. In addition to adhering to privacy regulations, businesses should consider the ethical implications of Robo-advisors' data privacy. Regular security audits and updates can assist in identifying vulnerabilities and enhancing the privacy of Robo-advisors' data. It is also essential to recognize that data privacy is not static and requires continuous monitoring and updates in order to remain secure. As hackers and other malicious actors develop new techniques to breach the privacy of Robo-advisors' data, Robo-advisors developers must stay abreast of the most recent privacy measures and alter their strategies accordingly. Regular privacy audits and revisions can assist in identifying vulnerabilities and enhancing the privacy of Robo-advisors' data (Yang et al., 2023).

Finally, it is essential to note that robot advisors are not immune to human error. Human employees who administer Robo-advisors may make errors that compromise data privacy(Awwal-Bolanta & Anakanire, 2025), such as mishandling customer data or failing to obtain customer consent. Therefore, businesses must ensure that their employees are trained in best practices for Robo-advisors data privacy and aware of the potential dangers of Robo-advisors. The importance of data privacy to the success of AI-based Robo-advisors in the business context cannot be overstated. Robo-advisor developers must prioritize data collection, data storage, and data sharing to guarantee that customer data is used ethically and with customer permission. Companies must adhere to privacy regulations and evaluate the ethical implications of Robo-advisors' data privacy. Regular privacy audits and updates can help identify vulnerabilities and enhance the privacy of Robo-advisors' data, whereas employee training can prevent human errors that compromise data privacy (Hasal et al., 2021). By prioritizing Robo-advisors' data privacy, businesses can develop consumer trust and preserve their positive reputation in the market (Fernandez, 2023).

Additionally, businesses should provide customers with plain and concise information regarding the data privacy policies of their Robo-advisors. This includes informing customers about the accumulated data, how it will be used, and with whom it will be shared. Additionally, businesses should make it simple for customers to access and administer their data through a customer portal or Robo-advisors interface. Compliance with privacy regulations such as the GDPR and CCPA is another essential aspect of Robo-advisors' data security. These regulations require companies to obtain customer consent for the collection and use of their data, to provide customers with access to their data, and to safeguard customer data from misuse and data breaches. Companies that fail to comply with these regulations may incur significant financial and reputational losses (AlBenJasim et al., 2023).

Additionally, businesses must consider the possibility of biases and discrimination in Robo-advisors' data. Robo-advisors trained with biased data can perpetuate biases and discrimination, negatively affecting consumers and the company's reputation (Abbas, 2024). Therefore, developers of Robo-advisors should take measures to mitigate these risks, such as using diverse and representative data sets and performing regular audits of Robo-advisors' data for bias. It is important to note that Robo-advisors are susceptible to data intrusions and cyberattacks (Edwards, 2024). Companies must ensure that their Robo-advisors are built with security in mind and implement security measures such as encryption and access controls to safeguard consumer information (Behera et al., 2021). Regular security audits and updates can assist in identifying vulnerabilities and enhancing the privacy of Robo-advisors' data. The importance of data privacy to the success of AI-based Robo-advisors in the business context cannot be overstated (Adam et al., 2021). Robo-advisor developers must prioritize data collection, storage, and sharing to guarantee that customer data is used ethically and with customer permission (Dinh & Park, 2024). Companies should comply with privacy regulations, provide customers with explicit information about the data privacy policies of their Robo-advisors, and consider the possibility of biases and discrimination in Robo-advisors data. In order to safeguard consumer data from data breaches and assaults, businesses should also prioritize Robo-advisors' security. By prioritizing Robo-advisors' data privacy, businesses can develop consumer trust and preserve their brand reputation (Ng & Zhang, 2025).

2.5 Technology Enabler

The most frequently utilized technologies in the customer service industry are big data analytics, artificial intelligence, machine learning (ML), Natural Language Processing, and Large Language Models (LLMs) (Bhattacharyya, 2024). The dilemma of facilitation through diverse needs in real-time, considering loyalty and experience in financial services, can be addressed through more efficient customer interactions with the help of LLMs (Kolasani, 2023).LLMs provide logical replies, making them beneficial in real-world scenarios. They also interpret complicated verbal patterns (Bharathi Mohan et al., 2024). Their development and implementation, however, raise ethical concerns and have societal ramifications. The popularity of Robo-advisors powered by Artificial Intelligence (AI) has increased in recent years, owing to the cost and time benefits they enable. However, due to its growing popularity, users may be less likely to comply with Robo-advisors' demands (Adam et al., 2021). Client experiences and consumer discontent on the front lines of service are improving as more robots with human-like characteristics (i.e., self-service machines) are utilized in the hotel sector to replace human labor, hence enhancing client experiences and reducing customer dissatisfaction (Fan et al., 2020; Yu, 2020). Robo-advisors powered by artificial intelligence (AI) can help many clients personally and efficiently while being more cost-effective and adaptive than traditional human agents (C. R. M. Schmitt, 2020). Because of technology improvements, product-centric business models are being replaced by service-centric business models (Soto Setzke et al., 2021). Home services offered by the Internet of Things (IoT) include security, entertainment, and assisted living, aiming to improve consumers' overall quality of life (Soto Setzke et al., 2021). Salespeople may leverage social media to aid them in carrying out service behaviors such as customer service to offer value (Dwivedi et al., 2021). Businesses must place a premium on customer relationship management to maximize the value of their service offerings to customers (Pradeep Kumar et al., 2021). Consumer engagement in product development and quality enhancement processes confers significant advantages to organizations by facilitating the creation of more valuable and feature-rich products and services for their clientele (Chatterjee et al., 2021).

"Beyond the hype" refers to providing superior, quicker, stronger, objective, and impartial results without the supervision of customer service professionals, which is precisely what this study accomplished. In our opinion, the supply of more accurate and timely information is the most critical function that information systems can perform. “Behind the Scene” by Jean Bédard and Yves Gendron (2004), Lomné et al. (2013), and "Beyond the Hype" (Gandomi & Haider, 2015; Ransbotham et al., 2016) are all instances of phrases with a specific definition.

To summarize, no study on Robo-advisors has examined how and whether cognitive technology can be harnessed to develop Robo-advisors, discussed personalization and contextualization in customer service, or described how a Robo-advisor could provide users with high-quality information.

2.5.1 Ethical Issues Large Language Models (LLMs)

Despite the impressive advancements and growing integration of Large Language Models (LLMs) into customer service frameworks, their deployment is not without ethical challenges. As these systems increasingly replace or augment human interactions, one of the primary concerns revolves around transparency and accountability. Customers interacting with LLM-powered Robo-advisors may not always be aware that they are communicating with non-human agents, raising questions about informed consent and potential manipulation, especially when the bot simulates empathy or uses persuasive language (Crawford & Paglen, 2021).

Moreover, LLMs often operate as "black boxes," making it difficult to trace how specific outputs are generated. This opacity becomes problematic when biased or incorrect information is provided to users, especially in sensitive domains like finance or healthcare. While LLMs can deliver personalized responses by interpreting vast amounts of customer data, such personalization often involves collecting and analyzing personal data at scale. This raises privacy concerns, particularly around data security, consent, and usage—issues that are often exacerbated by vague or inaccessible terms of service (Farag et al., 2024).

Another critical ethical issue is algorithmic bias. Since LLMs are trained on massive datasets scraped from the internet, they may inadvertently inherit and perpetuate societal biases, including those related to race, gender, or socio-economic status. In customer service, such biases can result in differential treatment of users, potentially reinforcing existing inequalities (Chen et al., 2024). Furthermore, as LLMs begin to take on roles that traditionally required human intuition and moral judgment, the lack of emotional intelligence or contextual sensitivity may lead to dehumanizing experiences, particularly in cases involving complaints, disputes, or distress (Walther, 2024).

Lastly, the replacement of human labor with AI-driven systems like LLMs also prompts broader questions about job displacement and the erosion of human-centered service cultures (Patel & Indurkhya, 2025). While efficiency gains are undeniable, organizations must consider how automation may impact employment and whether it aligns with their social responsibilities.

In conclusion, while LLMs offer substantial potential for transforming customer service through speed, scalability, and personalization, these benefits must be weighed against significant ethical concerns (Chkirbene et al., 2024). A balanced and responsible approach requires organizations to implement robust governance frameworks, conduct regular bias audits, and prioritize transparency and user autonomy in the deployment of these cognitive technologies.

2.6 Theoretical background

Robo-advisors, one of the most prevalent human-computer interactions (HCI), are undeniably successful (Eren, 2021b). Examining how Robo-advisors have been used in the past for customer support is critical. In recent years, businesses have increasingly depended on Robo-advisors to deliver customer assistance, mainly due to underlying technology developments (Ho, 2021). As a result, understanding how technology may be leveraged to increase customer happiness is crucial. A significant conclusion of the literature review is that customer service chatbots and technology enablers for customer service are two of the most critical areas to address. It is also vital to understand that cognitive technology adoption is defined as an individual's readiness to embrace and use novel technologies (Kamal et al., 2020). There are various widely accepted models of IT adoption, including the TRA (Kuo et al., 2015b), the D&M model (DeLone & McLean, 2003), the DOI model (Rogers et al., 2014), the TAM model

(F. D. Davis, 1989), and the UTAUT model (V. Venkatesh et al., 2003). Several IT-based apps were examined for efficacy using these models to ensure safety and success. Cognitive technology addresses just the technical components of information systems, such as software and development platforms (IT). Based on this, the theoretical framework for cognitive technology adoption and the Robo-advisors is presented. Among the TRA's critical weaknesses are its disrespect for cognitive deliberation and the critical issue of theory validation by voluntary application (Walters, 2022). It introduces two new complications to the model (Taherdoost, Namayandeh, et al., 2011; Taherdoost, Sahibuddin, et al., 2011). First, one's attitude toward technology is irrelevant if a concerned system is not readily available. When comprehending the six critical characteristics of an effective information system, D&M gives in-depth definitions and explanations for each word (DeLone & McLean, 2003). Much research has been conducted to determine if D&M can survive the success of Information Systems (IS) (Ashfaq et al., 2020; Rodriguez & Boyer, 2020). The TAM (Carter & Bélanger, 2005) is a well-known model for predicting technological acceptability and identifying the modifications that must be made to the technology to be accepted by users.
While businesses such as Google, Facebook, and Microsoft have expressed optimism about Robo-advisors, several critics have remarked that customer acceptance of current Robo-advisors is less than anticipated (Belanche et al., 2024). According to a recent poll conducted by LivePerson, Robo-advisors' adoption is limited, especially in technologically savvy countries such as the United States (Sugumar & Chandra, 2021). Despite the enormous potential of artificial technologies in the financial sector (Jang et al., 2021), Robo-advisors have not yet attracted the attention of consumers in this segment; therefore, we define our research in terms of the adoption of Robo-advisors by financial institutions such as banks and insurance companies. While higher implementation costs motivate businesses to seek returns on their investments, the rewards are now restricted due to consumers' poor adoption of Robo-advisors (Sugumar & Chandra, 2021).

TAM was also viewed as a foundation for technology research (Avlonitis & Panagopoulos, 2005). The TAM and D&M models have been integrated (Ashfaq et al., 2020; Rodriguez & Boyer, 2020). According to Ashfaq et al. (2020), Robo-advisors may be used with human customer service representatives to satisfy online clients. To our knowledge, no studies have been conducted to illustrate the impact of Robo-advisors on customer service in terms of TAM and D&M models.

2.6.1 Technology Acceptance Model (TAM)

Researchers in Information Systems (IS) have developed and tested several theories and models drawn from psychology, sociology, and communication to better understand and foresee how end-users would interact with and use IT (Tarhini et al., 2016). Examples include the Cognitive Model (COG) by (Oliver, 1993), the Theory of Planned Behavior (TPB) by Icek Ajzen (1985), the Technology Acceptance Model (TAM) by F. D. Davis (1989), the Information Systems Expectation Confirmation Model (ECM) by Mukhopadhyay et al. (2001), the Unified Theory of Acceptance and Use of Technology (UTAUT) by V. Venkatesh et al. (2003) and its extended model (UTAUT2) by Venkatesh (IS success model). The Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975; Vallerand et al., 1992) seems to be the most often utilized framework in analyzing technology adoption, especially among IS researchers (F. D. Davis, 1989; Davis et al., 1989). According to TAM, users' perceptions about an information system (IS) affect their desire to utilize it. Perceived ease of use (how much a person thinks utilizing a specific system will be without effort) and perceived utility (how much a person believes using a particular system would improve their work performance) are also essential to TAM's explanation of user intention variation.

Despite its widespread use in investigating technology adoption for tourism (Buhalis et al., 2024), it has been argued that TAM's fundamental constructs (perceived ease of use and perceived usefulness) do not fully reflect the parity between the benefits and costs of implementing new technology (Moon & Kim, 2001). Due to the difficulties in human-AI Assistant interaction discussed above, factors other than the perceived utility of AI Assistants and the ease of using the system may be responsible for users' acceptance and readiness to utilize the new AI Assistant technology. In fact, (Bhattacherjee, 2001; Bhattacherjee et al., 2008) argued that the success and long-term effectiveness and viability of an IS depends on its continued use rather than its initial acceptance/use and that the acceptance phase of IT usage includes unique factors like expectations, confirmation, and subsequent satisfaction. It is reasonable to infer that users' adoption intention of AI Assistants and readiness to interact with technology will be influenced by users' expectations of the system, including the intelligence level of AI Assistants and whether or not the actual performance satisfies users' expectations. Newer studies have added context-specific constructs to TAM to improve its explanatory power. These include 'trust' in the online shopping context (Gefen et al., 2003), 'perceived credibility' in reflecting ‘security and privacy concerns' in the online banking context (Liu &

Wang, 2003), 'anthropomorphism' (Blut et al., 2021), and 'perceived enjoyment' (Koufaris & Hampton-Sosa, 2002).

Despite this, several research studies have demonstrated why TAM is insufficient/weak in explaining the connection between technology and its actual growth and use (Song et al., 2021; Sorce & Issa, 2021). For instance, prior research, e.g.,(Alsyouf et al., 2023; Martín-García et al., 2022) showed that TAM could not supply all of the factors that lead to mobile phone use, such as the social influences and enabling environments. TAM is insufficient to explain the acceptance and usage of new technology in the e-government environment (AlHadid et al., 2022). The Technology Acceptance Model (TAM) has been used in several studies to explain why people plan to use new technologies. However, an oversimplified framework fails to account for unique contextual factors that may influence people's propensity to accept new tools. Different technological, organizational, and environmental factors were discovered to affect AI adoption by (J. Xu et al., 2021). When it comes to adopting new technologies, not only do external circumstances matter, but so do individual user traits. To effectively address the desire to embrace new technologies, (Emaeilzadeh et al., 2014) proposed to include user-specific variables in the IT adoption model.

Therefore, in this thesis, TAM cannot be utilized alone to explain user acceptability and intention to use AI assistants. The characteristics of users (in this case, fintech Robo-advisors users) and the financial context need to be considered in order to modify or further develop the model into a fintech Robo-advisors adoption model. It is essential because the technology requires high intelligence to build satisfying interactions, and financial transactions and services are inherently complex processes.

2.6.2 Information System Success Model (IS Success Model)

System and McLean's original Information System Success Model from 1992 claimed that system quality and information quality affect utilization and user happiness, leading to individual and organizational impact. DeLone and McLean (2003) revised their original model. They proposed an updated version that posits three critical factors influencing user satisfaction: information quality, system quality, and a newly added construct: service quality. Over 300 studies were based on this model in the following decade. Another dependent variable, future intent to use, was considered alongside usage and satisfaction. The individual and organizational effects have also been taken out of this model. In its place, the "net benefits" variable was introduced as a reaction to the literature's critique that IS impacts might extend beyond the person and organizational levels.

However, the IS success model has rarely been tested for AI Assistant technology, especially in the context of travel (Dhiman & Jamwal, 2023). Therefore, the model has significant potential to solve concerns of satisfaction and usage purpose in human-AI Assistant interaction due to the importance of the notions it incorporates. It has been hypothesized that user happiness is a significant factor in people's propensity to continue using technological solutions. Understanding the antecedents of user happiness can help us understand how to motivate people to use AI assistants. It is significant since user satisfaction is crucial in explaining how users perceive and assess the AI assistant system. According to Naseer et al. (2020), consumers' contentment has a beneficial effect on their propensity to employ a Robo-advisors e-service. It is suitable to utilize the IS success model as the theoretical basis to create an initial model of this study because user satisfaction and use intention are major dependent variables in the IS success model and because various quality characteristics are addressed in the IS success model.

However, the new IS success model differs most significantly from the aforementioned TAM because it explains user happiness and satisfaction's role in driving intent to use. However, research on the effects of technology on people's lives finds that the model falls short when it comes to evaluating user-related factors such as subjective norms, personalities, attitudes, and trust (FakhrHosseini et al., 2024). Both demographic characteristics (such as age, gender, and technical knowledge) and psychological elements (such as cognitive, hedonic, and intrinsic motivation) are important in determining why users are happy with and excited to use a certain technology. Dinh and Park (2024) show that hedonic motivation favors the intention to use voice assistants. In contrast, Tojib et al. (2022) find that intrinsic motivation positively drives consumers' desire to utilize service robots. As a result, this model is insufficient to comprehend the drivers of user satisfaction and behavioral intentions toward AI Assistants/ Robo-advisors in Fintech; instead, the researcher should combine this model with another framework that accounts for user-related elements.

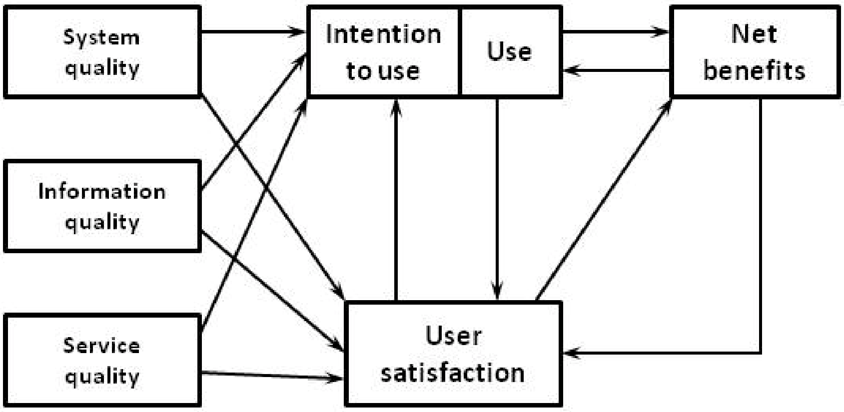

Figure 3: Updated Information System Success Model

(DeLone & McLean, 2003)

2.6.3 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The Unified Theory of Action, Use, and Transition (UTAUT) model combines eight other models into a single framework: the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1988), the Technology Acceptance Model (TAM) (Davis, 1985), the Motivational Model (MM) (Davis et al., 1992), the Theory of Planned Behavior (TPB) (V. Venkatesh et al., 2003). Four independent variables—age, gender, experience, and voluntariness of use—and four moderating variables—performance expectation (PE), effort expectancy (EE), social impact, and enabling conditions—comprise the UTAUT model.

UTAUT is an effective model for researching how people feel about various technologies, although it does have certain restrictions (Negahban & Chung, 2014). Due to its origins in explaining technology adoption and usage in the workplace, the UTAUT model's applicability to the realm of consumer technologies is an area that needs further scrutiny. To address this, Venkatesh et al. (2012) revised the original UTAUT model to UTAUT2 (see Figure 8), which focuses more on customers' individual perspective/context. Three new constructs (hedonic motivation, price value, and habit) were introduced to the UTAUT2 model, while one moderating variable was removed (voluntariness). Compared to its predecessor, the UTAUT2 model significantly increases the variation explained regarding behavioral intention and technology use (Venkatesh et al., 2012). The revised UTAUT2 model gives better explanations for technology usage and behavioral intention than UTAUT, as further supported by (Melián-González & Bulchand-Gidumal, 2020).

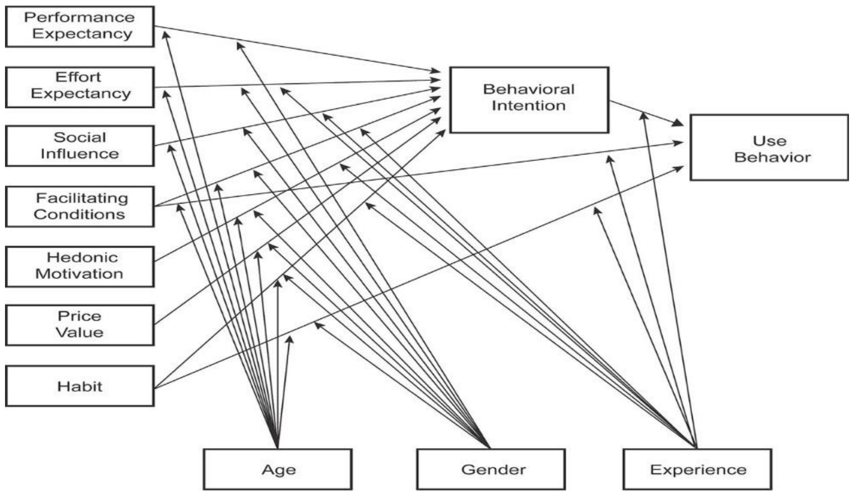

Figure 4: Unified Theory of Acceptance and Use of Technology (UTAUT2)

(Venkatesh, Thong, & Xu, 2012)

The UTAUT2 model has been used to describe the variables affecting technology adoption in a wide range of fields, including higher education (Almahri et al., 2020), healthcare (Yeoh & Chin, 2022), mobile payment (Hong et al., 2020), online banking (De Domenico et al., 2015), and service robots (Park et al., 2021). Melián-González and Bulchand-Gidumal (2020) and Kuberkar and Singhal (2020) are two examples of current research in the tourism and hospitality literature that employ the UTAUT2 model to investigate the factors that drive Robo-advisors adoption in travel. Users expect to have a pleasant conversation with a Robo-advisor, as shown by research by Melián-González and Bulchand-Gidumal (2020). Suppose the interaction process with a Robo-advisor is pleasant. In that case, many of the travelers' pleasurable objectives aimed at this interaction, such as booking a room and planning a trip for holidays, will be reinforced. The link between user happiness and other dimensions of behavioral intentions including the intention to use, suggest, and book trips was studied as part of the thesis in an effort to develop a new model. Findings also show that travelers anticipate Robo-advisors to function well when researching a topic, clearing up confusion, and tracking down a specific item or destination. More than that, they included the concepts of anthropomorphism and trust in their study because of the unique circumstances surrounding Robo-advisors' user engagement and the inherent value of human talks. In this thesis, we use anthropomorphism and trust to reflect the distinctive Robo-advisors usage environment since we observed that they both significantly affect the adoption intention of Robo-advisors.

However, the UTAUT2 model's enabling circumstances, social influence, price value, and habit were inappropriate for this investigation for a number of reasons. First, interacting with

AI Assistants is as easy as typing, talking, or doing a combination of the two, and there is no need for supplementary infrastructure to make this possible. Second, consumers may not have much experience with or current behavior in utilizing AI Assistants, and they may not be affected by their social networks when determining whether or not to use this technology; this is especially true in the context of travel. Also, the pricing implies users would have to pay to use the technology, while the commercial AI Assistants taken into account here are offered by service providers at no cost to customers. While the UTAUT2 model has been useful in identifying essential and distinguishing components impacting technology adoption intention in social contexts, and while it does encompass user-related factors such as hedonic incentive, it does not consider perceived hazards, privacy, or trust. These elements have been identified as crucial in shaping the likelihood of adopting and using a new technology (Rodríguez-Espíndola et al., 2022).

Recent studies on the diffusion of new technologies have expanded UTAU2 to account for additional privacy and perceived security characteristics that are technology-specific. It is reasonable to assume that factors such as system security, data privacy, and user trust all play a role in the decision to employ AI assistants in the context of this research. Due to the one-of-a-kind nature of AI Assistant systems and human-AI Assistant interactions, it will be crucial to factor in perceived intelligence as well. Perceived Information Quality is a significant factor in the growth of AI systems. Therefore, it will not be enough to utilize this model alone to investigate the factors that influence the development and utilization of AI Assistants. A new framework must be developed to better understand what aspects contribute to the widespread usage of AI assistants. As discussed previously, the UTAUT2 model serves as the theoretical foundation for this study, which also makes use of a few other constructs developed based on the findings of the thesis to investigate the factors that influence users' acceptance and behavior intentions when it comes to using AI Assistants for Fintech.

2.6.4 Acceptance of Robo-Advisors

Robo-advisors are unquestionably among the most efficient and widely utilized human-computer interaction technologies (HCI) (Eren, 2021a). Therefore, it is essential to investigate how Robo-advisors have been implemented in customer support. Organizations increasingly utilize robo-advisors to deliver customer assistance, partly due to underlying technological breakthroughs (Ho, 2021). Therefore, it is essential to comprehend how technology may aid in providing better client service. The literature review therefore, focused on two topics: technological enablers for customer service and Robo-advisors in customer care. Recent studies have explored the possible benefits of Robo-advisors for customer service in various industries. Liu and Stynes (2020) developed a novel approach utilizing a multi-turn answer activating model to improve the accuracy of Robo-advisors' responses and prevent misleads during customer interactions. Sarbabidya and Saha (2020) investigated the importance of customer service in the banking sector and evaluated the feasibility of online banking as a means of expanding businesses. The use of Robo-advisors powered by artificial intelligence (AI) has been advocated by Prabu et al. (2020) as a way to provide faster and more precise customer support.

Sheahan and Lamont (2020) examined the relationship between misunderstanding and customer acceptance of Robo-advisors, highlighting the importance of reducing errors to achieve adoption. Meanwhile, Chung et al. (2020) discovered that Robo-advisors e-service has the potential to provide immersive and engaging customer assistance, with user trust influenced by both Robo-advisors -related factors (e.g., its appearance, advice perception) and service-related factors (e.g., brand reputation, security). L. Xu et al. (2021) suggested that Robo-advisors could offer a new opportunity to personalize and scale customer attention, benefiting both businesses and customers. However, despite these promising findings, there is a need for further research to explore the potential of Robo-advisors for personalized and contextualized customer care. In recent years, advanced technologies, such as machine learning, big data analytics, and artificial intelligence, have offered new opportunities for improving customer service practices (Jaakkola et al., 2015; Lee & Lee, 2020). While adopting AI-powered Robo-advisors has been driven by the potential for cost and time savings, these options may not always meet customer expectations, leading to lower compliance (Adam et al., 2020). Some industries, such as hotels, have used humanoid robots to alleviate concerns and customer experiences (Fan et al., 2020; Pozharliev et al., 2021; Yu, 2020). As virtual assistants, Robo-advisors have appeared as a promising solution to serve a significant sum of customers in a personalized and efficient manner at a lower cost than human agents (B. Schmitt, 2020).

Furthermore, businesses are pursuing digital transformations to shift towards service-centric models, aided by developing technologies such as IoT-based smart home services that aim to improve the quality of life for customers (Sequeiros et al., 2021). Social media has also developed as an important tool for salespeople to engage in customer care and increase the value of their service offerings (Dwivedi & Wang, 2022; Kumar et al., 2023). Companies can leverage customer feedback to design new goods, including services and products with greater features and functionality, during the product development and quality improvement stages (Chakrabortty et al., 2023). Considering the study, the term "beyond the hype" refers to presenting research findings that are superior in speed and strength and impartial and unbiased. Information systems play a crucial role in providing fast and objective insights. The idioms "behind the scenes" (J Bédard & Y Gendron, 2004; McCahery et al., 2016) and "beyond the hoopla" (Buyruk & Güner, 2022) have specific meanings. Indeed, this study considers the requirement for future studies to focus on personalization and contextualization in chatbot-based customer service, the use of cognitive technology to develop Robo-advisors, and how these Robo-advisors can deliver a feasible quality of information to customers.

"Personalization" is tailoring a company's interactions with individual clients using various technologies and customer data. In order to enhance customer service, this study proposes integrating it with a Robo-advisor as opposed to a flow-based bot. To respond to user inquiries, Robo-advisors utilize natural language processing (NLP) techniques and various types of deep learning (DL) algorithms, including deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Although the creation of an intelligent chatbot for customer support is not within the scope of this study, Technology acceptance is a significant component in adopting and using new technologies, such as cognitive technology (Kamal et al., 2020). User capability is also essential for effective technology adoption and usage (Aggelidis & Chatzoglou, 2009). Several models have been used to study technology acceptance, including the "Theory of Planned Behavior" TPB (I Ajzen, 1985), The "Theory of Reasoned Action" TRA (Kuo et al., 2015a), the "Technology Acceptance Model" TAM (F. Davis, 1989), the "Diffusion of Innovations Theory" DOI (Rogers, 1995), and the "Unified Theory of Acceptance and Use of Technology" (UTAUT) (DeLone & McLean, 2003). However, some of these models have limitations and may not be suitable for certain investigations. For example, the TRA does not address cognitive deliberation and usage voluntariness (Loo et al., 2023), while the DOI focuses mainly on system properties, organizational characteristics, and environmental factors (Behera et al., 2024). The UTAUT has been found to be effective in measuring consumer adoption of mobile health applications in government service delivery (Alam et al., 2020) but may not be suitable for other contexts. To address these limitations, researchers have integrated different models to better understand technology acceptance and usage. TAM has been found to be a highly effective paradigm for technology adoption, particularly in predicting client acceptability and highlighting aspects of technology that must be improved before it can be deemed acceptable (Carter & Bélanger, 2005). The TAM model has also been integrated with the "DeLone and McLean" (D&M) model, which provides an inclusive recognition of "information system" (IS) success by identifying and articulating the connections between the six key aspects of IS success: "information quality" IQ, "system quality" SYQ, "service quality" SRQ, "system use/usage intentions" UI, "user satisfaction" US, and "net system benefits" NSB (DeLone & McLean, 2003). The integration of the TAM and D&M models has been examined in various studies (Ashfaq et al., 2020; Pereira et al., 2020; Zaied, 2012), but no empirical research has evaluated the influence on customer service considering Fintech viewpoint by Personalized Robo-advisors, integrating these models. Therefore, there is a need for further research to examine the combination of the TAM and D&M models in the perspective of a Robo-advisors for Fintech customer service. This research can interpret the valuable insights considering the factors that affect TAM and usage in this context and highlight areas for improvement in the design and implementation of Robo-advisors for Fintech customer service.

3. Research overview

As the understudy's product is tied to the financial industry, data privacy, security, and trust sensitivity is amplified. Thus, this research aims to analyze Robo-advisors users'/investors' perspectives on and acceptance of Robo-advisors. Connecting to the literature review mentioned, the current research requires an examination of issues such as trust, security, and privacy within financial institutions in Robo-advisors usage context and their held beliefs that may influence acceptance.

There are two levels of problem statements, level 1 (Kasilingam, 2020; Murtarelli et al., 2021) and level 2 (Rese et al., 2020) (Aslam et al., 2022) (Araújo & Casais, 2020), identified :

Level 1, there is a need to address the problem of customers of financial services regarding trust, security, and privacy.

Level 2: Users of financial services are less accepting of Robo-advisors and less likely to employ them.

Following are the research objectives in the context of the above two prescribed problems,

- Firstly, I investigate how Robo-advisors address the issues of trust, security, and privacy of data for investor/ Robo-advisors' users.
- Secondly, I investigate what factors are significant to the perceived competence of Robo-advisors for acceptance and usage by the investors/ Robo-advisors' users.

According to the research objectives and problem statements, I formulated the following three research questions:

> RQ1 How do Robo-advisors address the problems of trust, security, and data privacy?
>
> RQ2 What is the effect of perceived competence on Robo-advisors' acceptance for users?
>
> RQ3 What are the factors that enhance perceived competence for Robo-advisor users?

On the basis of constructed research questions, I plan to use the following constructs.

3.1 Constructs and Definitions

Table 1: Definition of constructs

Perceived Trust (PT)	"Perceived Trust (PT) is the person's belief, confidence, and expectation about the trustworthiness of a Robo-advisor."	(Chen, 2006; Kasilingam, 2020)
Perceived Risk (PR)	"Perceived Risk (PR) It is the consumer's perceptions of uncertainty and the negative consequences of Robo-advisors usage."	(Dowling & Staelin, 1994; Trivedi, 2019)
Perceived Information Quality (PIQ)	"It is the favorable cognitive beliefs about the Information Quality of Robo-advisors, such as accuracy, precision, completeness, significance, and relevance."	(DeLone & McLean, 2003)
Perceived System Quality (PSYQ)	"It is the favorable cognitive beliefs about the quality of the features of Robo-advisors, such as usability, availability, adaptability, and reliability."	(DeLone & McLean, 2003; Trivedi, 2019)
Perceived Service Quality (PSEQ)	"It is the favorable cognitive beliefs about the quality of the service of Robo-advisors such as responsiveness, assurance, and empathy."	(DeLone & McLean, 2003; Trivedi, 2019)
Customer Experience (CE)	"It is the degree to which the customer perceives that the Robo-advisors have effectively provided the PCCS that meets the individual need in the context in which the customer is aware of and/or using the product or services."	(Trivedi, 2019; Verhoef et al., 2009)
Perceived Ease of Use (PEU)	"It is defined as the degree to which individuals perceive how easy it is to use cognitive technology for the Robo-advisors implementation."	(F. D. Davis, 1989; Kasilingam, 2020)
Perceived Usefulness (PU)	"It is defined as the degree to which individuals believe that using the Robo-advisors that is built on technology would enhance job performance."	(F. D. Davis, 1989; Kasilingam, 2020)
Attitude Towards Technology (ATT)	"It is defined as an individual's positive feeling towards using cognitive technology for the Robo-advisors implementation."	(F. D. Davis, 1989; Kasilingam, 2020)
Intention to Adopt (ITA)	"It is defined as the degree to which the business adopts cognitive Robo-advisors to improve PCCS."	(F. D. Davis, 1989; Kasilingam, 2020)

3.2 Hypotheses overview

Typically, research begins with the identification of a problem. In addition to providing a specific repetition and clarification of the issue statement/research question, objective aims and hypotheses are also useful. It is possible to test a hypothesis by conducting extra research into it. A hypothesis is a preliminary explanation that accounts for a set of data. As defined by the scientific method, hypotheses should be comprised of claims suggesting a link between two or more measurable variables. The study is not limited to the hypotheses below. The factors are expected to be enhanced after the first phase of the interview analysis. I defined the following hypotheses related to the TAM and the DeLone & McLean models.

TAM model-related hypotheses

H1: “Perceived Ease of Use positively affects Attitude Towards Technology.”

H2: “Perceived Usefulness positively affects Attitude Towards Technology.”

H3: “Perceived Trust positively affects Attitudes Toward Technology.”

H4: “Perceived Ease of Use, Perceived Usefulness, and Perceived Trust positively mediate with Attitude Towards Technology to Intention to Adopt Robo-advisors.”

DeLone & McLean Model hypotheses

H5: “Perceived Information Quality positively Affects Customer Experience”

H6: “Perceived System Quality positively Affects Customer Experience”

H7: “Perceived Service Quality positively Affects Customer Experience”

H8: “Perceived Risk moderates the effect of Perceived Information, System, and Service Quality on Customer Experience.”

H9: “Customer Experience mediates the effects of Perceived Information, System, and Service Quality to the Intention to Adopt Robo-advisors.”

The hypotheses pertaining to the Technology Acceptance Model (TAM) concentrate on the determinants affecting user attitudes and their desire to embrace Robo-advisors. H1 and H2 assert that perceived ease of use and perceived utility are fundamental factors influencing people's favorable views toward technology. When people regard technology as user-friendly and beneficial for their work, their disposition towards its adoption is enhanced. H3 posits that perceived trust significantly influences attitudes. Individuals are more inclined to embrace technology when they have confidence in its secure operation and data protection capabilities. H4 integrates these components, asserting that perceived ease of use, utility, and trust collectively moderate the association between a favorable opinion toward the technology and the desire to embrace Robo-advisors. If consumers see Robo-advisors as user-friendly, beneficial, and reliable, they are more likely to develop favorable views, therefore resulting in the desire to embrace Robo-advisors.

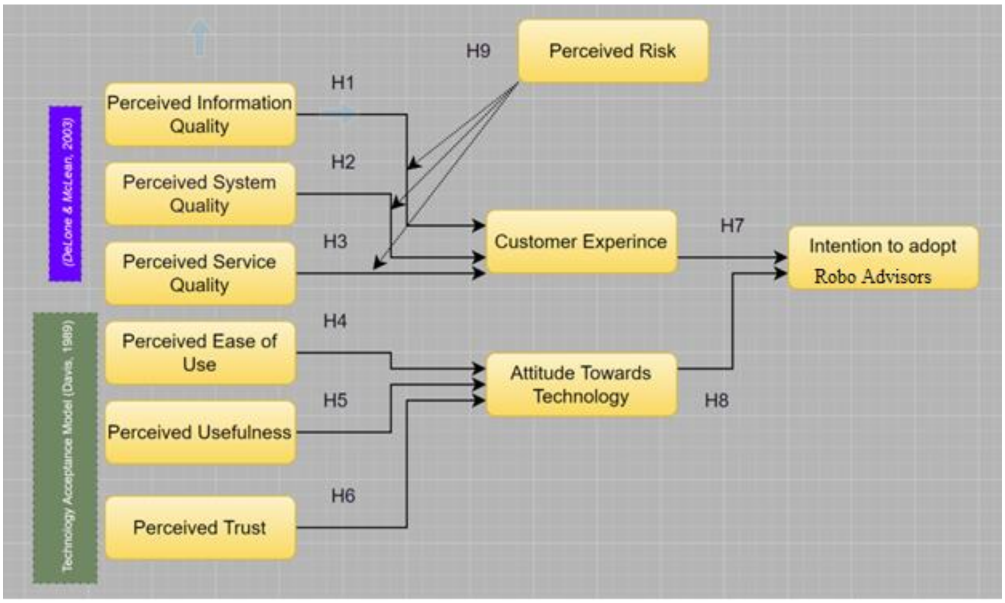

Figure 5: Technology Acceptance Model 1989 and DeLone & McLean Model, 2003

Note: model extension will also be done with the help of TAM3 and UTAUT 2 models because those are recent models.

The hypotheses established from the DeLone and McLean Model examine the influence of information, system, and service quality on customer experience and, consequently, the adoption of Robo-advisors. Hypotheses H5 to H7 propose that perceived information quality, system quality, and service quality benefit customer experience. Users are more inclined to have a positive experience when the Robo-advisors deliver precise, dependable information, operate well, and provide superior service. H8 posits that perceived risk serves as a moderating variable, indicating that despite high perceived quality, consumers' apprehensions regarding risk (such as data security or system failure) may mitigate the beneficial impact of quality on the entire customer experience. Ultimately, H9 posits that customer experience is a mediating variable between the perceived quality of information, systems, and services and customers' propensity to embrace Robo-advisors. A favorable customer experience is a critical factor in customers' decisions to use Robo-advisor technology, shaped by their assessments of the system's quality and efficacy.

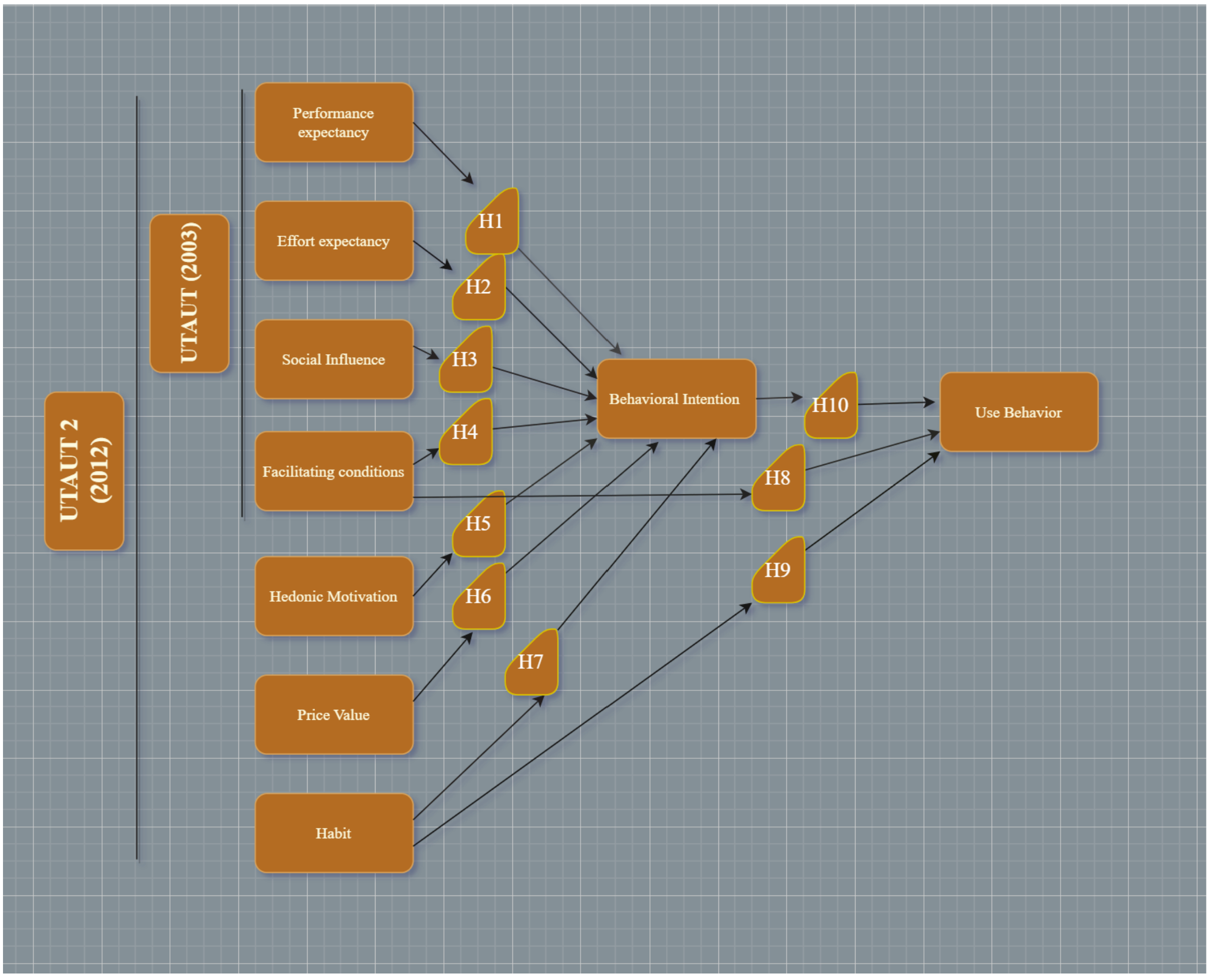

Figure 6: Base Model 2 Based on UTAUT 2

UTAUT 2 (2012) (extension of UTAUT 2003) was used to identify the behavioral intention and use behavior as a base model 2, which also helped to construct model 3 and model 4 further with the combination of base model 1 and base model 2.

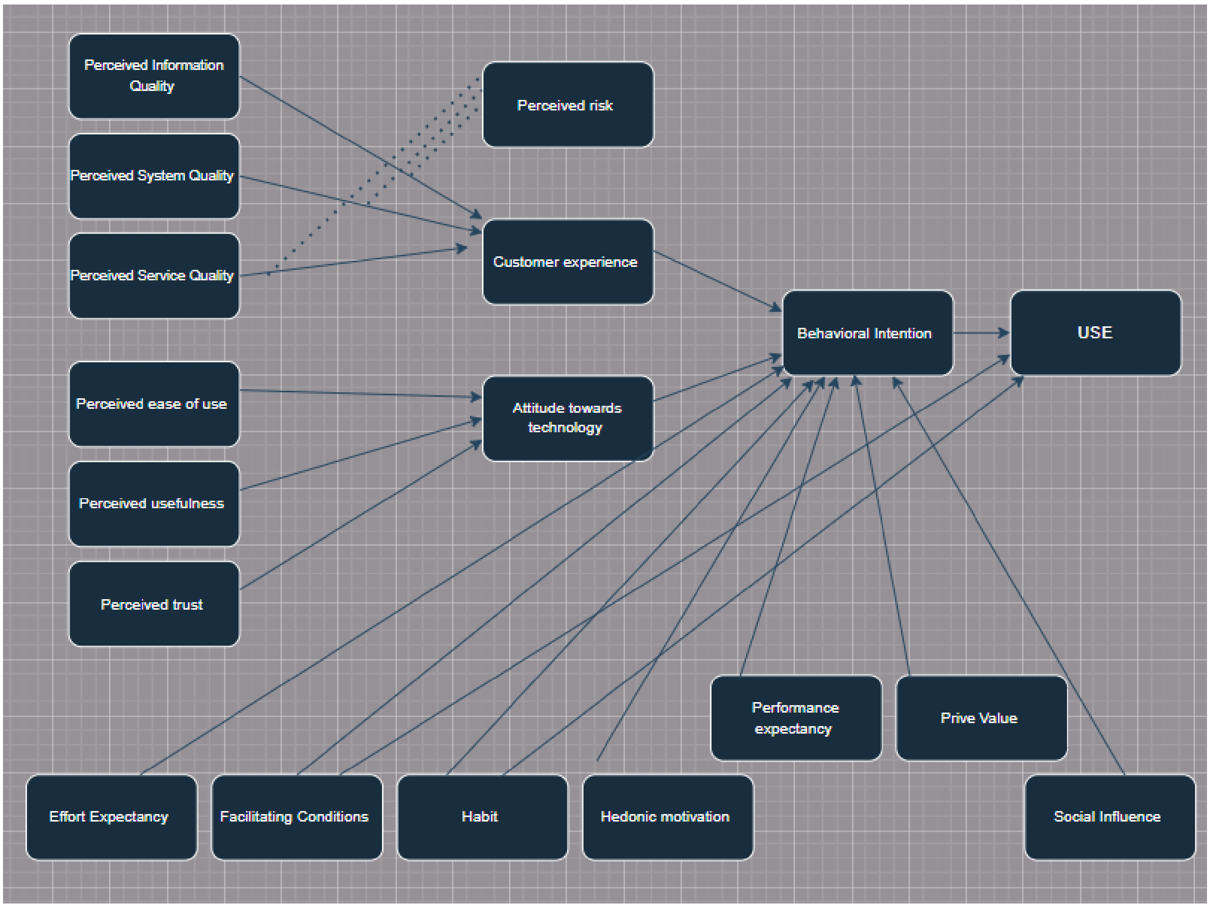

Figure 7: Model 3 Based on TAM, D&M and UTAUT2

Figure 7 illustrates Model 3, where the TAM, D&M, and UTAUT 2 models help to identify the intention and behavior of users of robo-advisors.

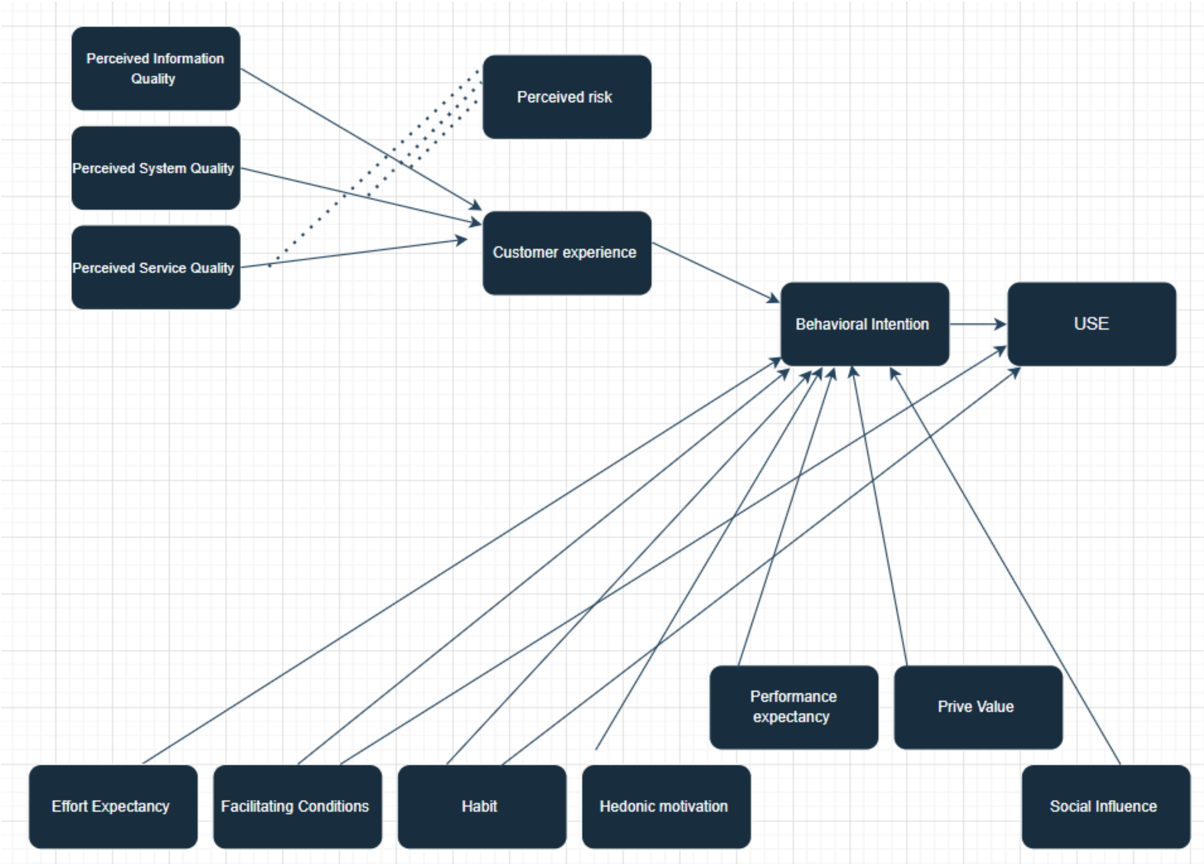

Figure 8: Model 4 Based on D&M and UTAUT2

Figure 8 illustrates the model 4 of the quantitative part. This model combines D&M and UTAUT2 to identify the behavioral intention and use of robo-advisors.

Overall Research Flow The following model explains the thesis's overall research flow. It started with the problem statement, followed by the methodology used, a mix of methods explanation, findings, and conclusions.

The study framework depicted in the image offers a thorough methodology for comprehending Robo-advisors' adoption by considering both user and investor viewpoints, especially within the realm of financial services. The framework delineates two principal degrees of concern. Level 1 underscores the necessity of tackling the fundamental challenges users encounter, including trust, security, and data privacy, which are vital in the financial industry because sensitive information is frequently transmitted. Level 2 underscores the hesitance of financial service consumers to embrace Robo-advisors due to these apprehensions, indicating a disparity in the acceptability and deployment of Robo-advisors technology within this sector. This delineates the overarching background of the study, emphasizing how enhancing perceptions of trust, security, and expertise may elevate Robo-advisors' adoption rates.

The research questions (RQ1, RQ2, and RQ3) direct the inquiry into the ways Robo-advisors might surmount these challenges. The graphic delineates the theoretical frameworks and structures employed to examine these challenges. The framework comprises classic models such as the Technology

Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and DeLone & McLean's Information Systems Success Model, in addition to contemporary notions like SELF theories and the Stimulus-Organism-Response (SOR) model. These models will be utilized to analyze how factors such as perceived simplicity of use, perceived utility, trust, information quality, system quality, and service quality influence users' views and their eventual intention to embrace Robo-advisors. The chapters in the framework are methodically arranged to analyze these structures, emphasizing data privacy, security, and trust, so ensuring a comprehensive examination of both technical and user-centric issues in Robo-advisors adoption.

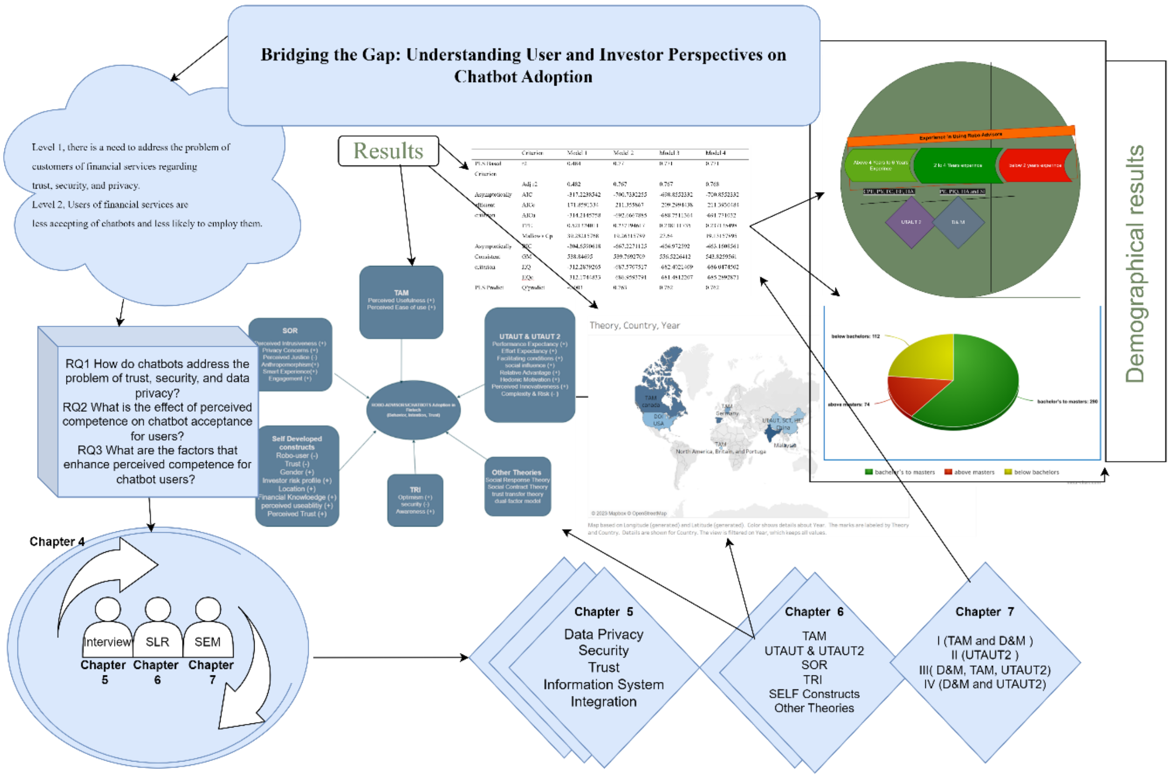

Figure 9 : Research Framework (source: Author)

4. Research Methodology

Consequently, there is a blend of qualitative and quantitative methods to achieve the research objectives, and I have chosen to use a mixed research approach to pursue the goals. This approach enables the researcher to gather and evaluate both quantitative and qualitative data inside the same study, resulting in a broader perspective for a more thorough output.

As I mentioned, my choice of methodology is a mixed method because it suits my research objective. In the first stage, I will incorporate qualitative semi-structured interviews with Fintech managers using Robo-advisors. The aim is to explore users' prevailing considerations and held behavioral beliefs regarding using Robo-advisors. Social representations theory (SRT) (Moscovici, 1984) will be considered as the basis for the first part of the research, in which semi-structured interviews are conducted with managers.

Due to the following reasons, SRT is being considered to be employed:

The theory focuses on social objects collectively. Individuals are considered part of the collectivity (Augoustinos & Walker, 1995); this can be a social guide for the community members to understand the collective knowledge (Moscovici, 1984). Therefore, SRT will work as the theoretical framework to understand the managers' shared understandings regarding Robo-advisors' services.

Secondly, SRT investigates the unfamiliar or novel social phenomenon and how it's being collectively anchored by community members to become concrete. As Wagner et al. (2002) invested in biotechnology, social representation caused debate about its consequences at that time. Organ donation (Barbier et al., 2020) and Fintech (Kumar & Rani, 2024) were also explored using the framework of SRT. A Robo-advisor is a relatively new technology, particularly in actual customer care, and hence is novel to stakeholders (i.e., customer managers). Thus, SRT, which may explain collective cognition about a novel or unfamiliar social object, may be an effective technique for examining managers' collective understandings of the new customer service enabled by modern IT.

Thirdly, SRT has been extensively employed in exploratory research. To comprehend the multifaceted nature of social representations, researchers have used a variety of exploratory approaches, and the theory's rich exploratory background has made it successful in tracing a collectively constructed social reality (Jang et al., 2021). Because financial Robo-advisor services are still in their infancy, I felt that an exploratory approach rather than a confirmatory strategy was more appropriate. As a result, I adopted the SRT theory, which has been extensively used in exploratory designs.

The research leads toward the second quantitative research stage based on these exploratory findings. At this stage, the study will empirically test the models and measure factors that affect the acceptance of Robo-advisors. Moreover, different relevant theories will be selected at this stage to provide the base for the identified factors from the first stage. As for now, TAM and D&M models are proposed for use at this stage. Through comparison, it will be analyzed which model explains the phenomena better and will help to comprehend the problem in a way that solves it.

Table 2: Research Methodology

No	Objective	Type	Techniques & Methods	Tools	Chapters
1	Fintech Managers and Staff Interviews to identify the factors	Qualitative	Semi-Structured Interviews	NVivo	5
2	Theoretical background identification	Qualitative	Systematic Literature Review	Rayyan/vosviewer	6
3	Model construction to identify the factors related to Robo-advisors' acceptance	Quantitative	Structural Equation Modelling (SEM)	Smartpls/ Adanco/ R	7

For Objective 1, which seeks to discover the variables impacting Robo-advisors' adoption via interviews with Fintech management and personnel, semi-structured interviews are the most suitable methodology. This methodology facilitates a comprehensive examination of participants' experiences and insights while preserving a flexible framework that enables the researcher to investigate specific topics, like trust, security, and data privacy. Semi-structured interviews are appropriate for this research since they enable participants to address both predetermined subjects and introduce unforeseen, pertinent elements. The qualitative technique employed addresses the intricate and context-dependent aspects of Robo-advisors adoption in the financial sector, facilitating a thorough comprehension of industry-specific issues. NVivo facilitates data analysis by enabling rapid coding and theme analysis, hence assisting in the organization of complicated qualitative data. This method is optimal since it gathers comprehensive, nuanced information that may be overlooked in more inflexible or exclusively quantitative approaches, enabling an in-depth examination of critical aspects from the viewpoint of industry experts.

Objective 2 utilizes a Systematic Literature Review (SLR) to ascertain the theoretical framework pertinent to Robo-advisors' adoption. The SLR technique is the optimal strategy since it offers a thorough and impartial synthesis of the existing literature, guaranteeing that the study is anchored in accepted ideas and highlights current gaps. The review employs systematic approaches to meticulously identify, assess, and analyze pertinent papers in a reproducible manner. This is essential for establishing a robust theoretical framework for the study and ensuring that the model development is guided by the most pertinent discoveries in the discipline. Instruments such as Rayyan facilitate the efficient screening and classification of extensive literature, whereas VOSviewer aids in visualizing topic clusters elucidating relationships among diverse study fields. This systematic method surpasses conventional literature reviews by reducing selection bias and guaranteeing thorough subject coverage, rendering it the most dependable means of identifying essential themes and gaps in the literature.

Objective 3 uses Structural Equation Modelling (SEM) to develop and evaluate a model that identifies the determinants of Robo-advisors' acceptance. Structural Equation Modeling (SEM) is the most suitable approach for this purpose since it enables the concurrent examination of various correlations among latent variables, including perceived ease of use, usefulness, and trust, which are fundamental to technology acceptance theories. Structural Equation Modeling (SEM) not only elucidates direct impacts but also encompasses indirect effects and intricate interactions among variables, rendering it optimal for hypothesis testing in investigations where several elements influence the adoption choice. SmartPLS, Adanco, and R are sophisticated tools for Structural Equation Modeling (SEM) that provide strong functionalities, including bootstrapping for statistical analysis and model validation. These instruments guarantee the model's precision and offer critical metrics such as goodness-of-fit indices to authenticate the structural linkages. In conjunction with these tools, SEM provides the most thorough and systematic approach for quantitatively assessing the model, assuring that the links established in prior qualitative phases are empirically substantiated. No alternative method provides the same degree of sophistication in evaluating large models with several latent variables, rendering it the optimal strategy for this research.

4.1. Semi-structured interviews

The interactions of financial services consumers with banking Robo-advisors will be investigated using qualitative interpretive methods (Bell et al., 2022). This method enables a more in-depth investigation of the topic, backed up with facts and stories (Cass & Faulconbridge, 2016). Researchers can gather qualitative insights to better grasp participants' experiences without putting rigid frameworks on them. Since participants are allowed some flexibility in responding to study questions based on a theoretical framework, the researchers can collect more relevant data (Mogaji et al., 2021). It is why semi-structured interviews are a productive part of the research plan.

4.2. Research design

As the topic of the study is identified as "Understanding User and Investor Perspectives on Robo-advisors Adoption in Fintech," the research aims to explore whether Robo-advisors address the problem of security and data privacy. How does perceived competence affect Robo-advisors' acceptance of users/investors? What are the factors that enhance perceived competence for Robo-advisors users/investors? During the first phase of the theoretical framework, numerous theories are under investigation in business informatics (Liu & Li, 2014). Most relevant and widely used theories will be considered for the research. Furthermore, the mixed method is deemed to be used according to the requirements of the study. Validity analysis will be considered for stage one, in which the management will take qualitative semi-structured interviews, whereas, in stage two, while considering empirical analysis, reliability and validity will be considered.

Considering the research design of the study philosophy adopted here, pragmatism is required as research questions are natural. Further, the research approach will be partly inductive in interviews, whereas the questionnaire part will be deductive. The methodological choice for this study is the mixed method as the study has two parts: the first part is for conducting the interviews, and the second part is for collecting the data by questionnaire. A Research Strategies survey and interview will be used. The time horizon of the study will be cross-sectional as it is intended to collect the data one time from the same respondents. However, if the study requirement changes in the future, it can be converted to a longitudinal study as per the requirement of study objectives. Data collection and data analysis techniques will be used as questionnaires and interviews. The sample frame is Pakistan and Hungary. Convenient and purposive sampling will be conducted for the interviews. On the other hand, snowball and purposive sampling techniques will be used for the questionnaire.

4.3. Data collection

Data collection will be done from semi-structured qualitative interviews with management, surveys from investors, and literature. In the first stage, the study will incorporate qualitative semi-structured interviews. The aim is to explore the prevailing ethical considerations of users and held behavioral beliefs regarding using Robo-advisors. The research leads toward the second quantitative research stage based on these exploratory findings. At this stage, the study will empirically test the models and measure factors that affect the acceptance of Robo-advisors. Data will be collected in the second stage of the questionnaire.

This study will gather data from Fintech Robo-advisors' users who employ Robo-advisors for financial services. These users may spend their money for various reasons and use a variety of investing methods, but the adoption of Robo-advisors is the primary focus of this study. Additionally, their perspective on Robo-advisors will be examined. If a consumer contacts the Robo-advisors for support or a question, it attempts to deliver as much information as possible.

The Likert scale questionnaire was intended for investors, and results were obtained via online interviews. The questionnaire's specifics are supplied. The scale for the constructs will be taken from the sources mentioned in Table 1.

In the first phase of the study, managers and employees of Fintech are interviewed using convenience sampling. This strategy is economical and well-recognized (Ruhl, 2004). The permission forms and information papers were sent to all respondents, which defined the study's goal. Depending on the interviewee's preference, the interview will be performed via video call or in person. Gifts or awards may be presented to respondents to increase the number of interviews, but additional aspects will be employed to eliminate any biases. After identifying the determinants, a questionnaire will be posted online, and responses will be collected using snowball sampling and purposive sampling. When Structural Equation Modelling (SEM) is utilized as a data analysis method, the sample size range should lie between 200 and 400 (J. Hair et al., 2006), and our focus will be on obtaining a larger sample size.

5. Robo-advisors in Fintech- Challenges and Solutions

In recent years, the banking sector has witnessed a transformative expansion in financial technologies, commonly referred to as Fintech. This paradigm shift, as noted by (Ediagbonya & Tioluwani, 2023), has significantly reshaped traditional banking services. Fintech, or financial technology, leverages algorithm-driven technology to streamline and automate the delivery of financial services, simultaneously spawning novel investment opportunities and revenue streams through innovative business models (Godavarthi et al., 2023). The evolution of Fintech, transitioning from analog to digital technologies, has predominantly been spearheaded by financial banking institutions. This technological revolution encompasses a diverse range of developments, including AI-enabled platforms, Blockchain, virtual currencies, crowdfunding platforms, Robo-advisors, Insure tech, and central bank digital currency (Ahmed et al., 2023; Lin & Chen, 2023). The rise of Fintech has ushered in an era of rapid, secure, and convenient financial services, increasingly preferred by consumers for transactions (Hsiao et al., 2022; Mogaji & Nguyen, 2022). Propelled by advancements in AI, machine learning, and big data analytics, this shift underscores the immense potential and promising future of Fintech in the realm of financial services (Langley & Leyshon, 2021; S. U. Rahman et al., 2023).

Robo-advisors have become an essential tool for businesses, especially in the banking and telecom sectors, in the rapidly growing digital landscape of Pakistan. Their adoption is motivated by the necessity to offer streamlined customer service and manage the growing influx of online interactions. Nevertheless, the incorporation of Robo-advisors raises substantial apprehensions around trust, security, and data privacy. In a country such as Pakistan, where the level of digital literacy is still developing and cybersecurity procedures are in their early stages, these issues are particularly noticeable. Users frequently exhibit reluctance to divulge personal information to automated systems due to concerns about potential data breaches and unauthorized utilization.

Trust is fundamental to the way users engage with Robo-advisors. Establishing this trust is imperative in Pakistan, considering the prevailing distrust towards digital platforms. Companies are improving the human-like interaction skills of AI-driven Robo-advisors to address this issue. Robo-advisors are being developed to comprehend and reply in local languages such as Urdu by utilizing advanced Natural Language Processing (NLP) and Machine Learning (ML) techniques. This enhances the user experience by providing a more personalized and relatable interaction. Furthermore, user trust can be established by transparent Robo-advisors’ operations, explicit communication regarding their functionality, and the presence of visible certificates or endorsements from reputable authorities. The growing emphasis on digitalization across numerous sectors in Pakistan has heightened the importance of security as a primary concern. In order to address this issue, corporations are incorporating strong encryption techniques and rigorous data protection procedures into their Robo-advisors systems. To ensure the privacy of user data, we implement routine security audits, strictly adhere to worldwide cybersecurity standards, and comply with Pakistan's regulatory framework for data protection. In addition, providing users with information about secure processes and the steps taken to safeguard their data is crucial in reducing concerns about data privacy.

Robo-advisors' future in Pakistan depends on achieving a harmonious equilibrium between technology progress and user-centered considerations. Advancing Robo-advisors technology in a secure and trustworthy manner will depend on the continuous enhancement of AI algorithms and the establishment of a robust legislative framework dedicated to AI and data privacy. Furthermore, using frequent feedback loops with users to comprehend their issues and customize Robo-advisor features accordingly will guarantee that these digital assistants are both technologically proficient and in harmony with Pakistan's cultural and social context. With the increasing digital awareness, Robo-advisors are expected to play a crucial role in the digital ecosystem, revolutionizing the way businesses engage with their customers.

5.1 Role of Robo-advisors in Fintech

Robo-advisors in the realm of financial technology (Fintech) are a notable advancement, aligning with the overall trends of automation and digitization in the Fourth Industrial Revolution (Mallisetty, 2023). Initially conceived as basic automated responders, Robo-advisors have advanced into sophisticated instruments driven by artificial intelligence (AI) and machine learning (ML) (Aggarwal et al., 2023). They possess the ability to proficiently manage intricate customer service responsibilities, such as addressing financial queries, overseeing account administration, and facilitating transactions (Dervishi et al., 2022). The incorporation of Robo-advisors into Fintech corresponds to the growing inclination of consumers toward digital-first engagements, wherein convenience and expedience take precedence (Poshtiri et al., 2024). Trust is a fundamental and essential aspect of the financial industry, particularly in the field of Fintech, where digital interfaces are used instead of human contacts (Sampat et al., 2023). In this particular setting, Robo-advisors encounter difficulty in establishing and preserving customer confidence. Research suggests that users' trust in Robo-advisors can be greatly influenced by their perceived intelligence and resemblance to humans (Felten et al., 2021). Fintech businesses are prioritizing the improvement of the cognitive capacities of Robo-advisors, aiming to make them more prompt and instinctive. The trust is influenced by the cultural background, especially in regions such as Pakistan. Adapting Robo-advisors to comprehend and engage in regional languages and cultural norms can greatly reduce the trust deficit (Ahmad et al., 2022).

Due to the sensitive nature of financial data, security is of utmost importance in the field of Fintech. Robo-advisors provide distinct security concerns as a result of their ease of access and the enormous volume of data they handle. In order to tackle these issues, Fintech organizations are implementing sophisticated encryption techniques, safe data storage solutions, and stringent authentication procedures within Robo-advisors systems (Zhou et al., 2022). Moreover, adherence to regulations, particularly in the areas of data protection and privacy, is of utmost importance. For Fintech organizations in Pakistan, it is essential to adhere to international standards and take into account local regulatory frameworks when utilizing Robo-advisors technology (Ahmed et al., 2021).

Data privacy in the finance industry, specifically in the functioning of Robo-advisors, is an additional crucial domain (Li et al., 2023). Transparent data regulations and user permission methods are necessary to address users' concerns regarding the utilization and dissemination of their data by Robo-advisors. Increasingly, Fintech organizations are adopting the practice of including privacy by design in Robo-advisors' creation. This approach prioritizes the protection of user data as a fundamental concept. Furthermore, providing users with knowledge about data privacy policies contributes to the establishment of trust in Robo-advisors' interactions (Haugeland et al., 2022; Li et al., 2021). So, the following research question can be constructed for further research analysis:

RQ1 How do Robo-advisors address the problems of trust, security, and data privacy?

5.2 Methodology

This section consists of two sub-sections. The first qualitative study was conducted on the basis of interviews collected from Pakistan, which used grounded theory and SRT. The second sub-section (Hungarian context) consists of 15 interviews collected from fintech experts in Hungary, for which TAM model and thematic analysis were used for the research to explore the role of AI assistants in Hungary.

5.2.1 Qualitative Pakistani Context (Semi-structured Interviews):

In this part/section of the study, we employed the Grounded Theory (Oktay, 2012) and SRT theory methodology to analyze how Robo-advisors in the Pakistani Fintech sector address issues related to trust, security, and data privacy. This qualitative research approach is particularly suited to our aim of developing a deep understanding of complex phenomena directly from the data.

5.2.1.1. Participant Selection and Snowball Sampling:

The study involved 34 participants, selected using snowball sampling, a technique well-suited for accessing specialized and interconnected populations like Fintech professionals. Starting with a few key informants identified through professional networks and targeted LinkedIn searches, the sampling expanded as these initial participants referred to additional interviewees within their networks. Grounded Theory (Stough & Lee, 2021) is a systematic methodology in the social sciences involving the construction of theories through methodical gathering and analysis of data. It is particularly effective for exploring areas with limited existing research or theoretical frameworks, making it apt for our study on the relatively new application of Robo-advisors in Fintech. Semi-structured interviews were used to collect data, allowing for open-ended responses while guiding the conversation toward specific topics. This format facilitated rich, detailed insights into the experiences and perceptions of Fintech professionals regarding Robo-advisors technology. Interview guidelines were carefully crafted to align with Grounded Theory principles, focusing on generating rich, qualitative data that could inform the development of new theories. The guidelines included open-ended questions to explore how Robo-advisors are being used in Fintech, the challenges and strategies related to trust, security, and data privacy, and the overall impact of Robo-advisors on the Fintech industry.

The choice to utilize Grounded Theory was driven by its inductive nature, allowing for the emergence of new theories and insights directly from the data rather than testing existing hypotheses. This approach is particularly suitable for the Fintech context in Pakistan, where the application of Robo-advisors technologies presents unique challenges and opportunities that might not be fully captured by existing theoretical frameworks.

5.2.1.2. Data Analysis Process

Consistent with the principles of Grounded Theory, the process of data analysis entailed a constant interaction between the gathering and processing of data. The transcribed interviews underwent coding, with the codes being consistently compared and refined to discern significant themes and patterns. The iterative approach was carried out until theoretical saturation was achieved, meaning that no new themes were identified from the data. This ensured a thorough and comprehensive comprehension of the subject matter.

The study utilized QSR NVivo software to code and conduct in-depth textual analysis, which is essential for organizing and analyzing qualitative data in Grounded Theory research. The analysis was organized into three distinct phases (Maleksadati et al., 2023). During the **open coding phase**, the main objective was to find important terms and concepts from the interview transcripts. **Axial coding**, the second phase, involved categorizing comparable concepts to facilitate the recognition of patterns and connections within the data. **Selective Coding**: The concluding stage was consolidating these categories into a cohesive coding hierarchy, which directed the meticulous examination of the data. A mind map was generated while coding to visually represent connections and alternative study paths, facilitating the development of a thorough comprehension of the concepts.

Figure 10 : Open Coding Phase Word Cloud

Word Cloud explains the word frequency to understand the major topics and discussions during the interviews. This word cloud is relevant to the coding of challenges.

Further themes were made in the open coding phase, and it can be seen that at the initial stage from 34 interviews, several codes were made; later, it was categorized into a few codes, and then it took the shape of themes.

Table 3 Profile of interviewee

Interviewee ID	Interviewee Gender	Age	Business Experience	Position
1	Female	35	10	Employee
2	Male	42	15	Manager
3	Female	38	12	Manager
4	Male	45	20	Director
5	Female	30	8	Manager
6	Male	40	14	Employee
7	Female	32	9	Manager
8	Male	50	25	CEO
9	Female	37	11	Manager
10	Male	48	18	CEO
11	Female	34	10	Manager
12	Male	39	13	Manager
13	Female	29	7	Manager
14	Male	52	28	CEO
15	Female	36	12	Manager
16	Male	46	22	CEO
17	Female	31	9	Employee
18	Male	43	17	Manager
19	Female	41	15	Manager
20	Male	38	14	Manager
21	Female	35	10	Employee
22	Male	47	20	Manager
23	Female	33	11	Manager/Researcher
24	Male	49	21	CEO
25	Male	39	14	Manager
26	Male	44	16	Manager
27	Female	30	8	Employee
28	Male	41	15	Manager
29	Male	37	13	Manager
30	Male	51	26	CEO
31	Female	34	10	Employee
32	Male	53	30	Manager

33	Male	42	18	Manager
34	Male	55	33	CEO

The profiles of the interviewees can be seen in the above-mentioned tables.

Table 4 Challenges behind the adoption of Robo-advisors in Fintech identified from the literature

Challenge	Sources
Trust	(Kasilingam, 2020; Ng et al., 2020; Pillai & Sivathanu, 2020; Rodríguez Cardona et al., 2021; Trapero et al., 2020)
Data Privacy	(Aw, Leong, et al., 2023; Rodríguez Cardona et al., 2021; Roh et al., 2023)
Security	(Roh et al., 2023; Zumstein & Hundertmark, 2017)

The emergence of Robo-advisors, which are automated investment platforms that employ algorithms and technology to offer tailored financial guidance, has fundamentally transformed the investment industry (Nain & Rajan, 2023). Nevertheless, the extensive utilization of Robo-advisors has been impeded by apprehensions regarding trust, data privacy, and security despite their capacity to democratize financial planning and enhance accessibility (Dhingra et al., 2021). These worries arise because of the delicate nature of financial information and the possibility of it being misused or compromised.

The question of trust is a fundamental difficulty in the adoption of Robo-advisors. Investors frequently have concerns about relying on algorithms and software systems to manage their finances, especially when dealing with large amounts of money (Bhatia et al., 2021). Acquiring consumer trust necessitates creating a reputation, showcasing transparency, and offering explicit explanations of investment reasoning and tactics. Robo-advisors gather comprehensive personal and financial information from users in order to customize investment suggestions (Wu & Gao, 2021). The presence of this data raises substantial privacy concerns, as it holds considerable value for identity thieves and other harmful individuals. To guarantee data privacy, it is necessary to implement strong security measures, establish explicit data handling policies, and provide transparent information about data-gathering activities.

Safeguarding user data from unauthorized access, tampering, or disclosure is of utmost importance when it comes to financial information. Robo-advisors are required to follow strict security measures, which involve implementing encryption, access controls, and vulnerability assessments. Regular system inspections and evaluations are crucial for detecting and resolving any security weaknesses.

Table 5 Solutions to adoption of Robo-advisors in Fintech identified from literature

Solutions	Sources
Educate	(Bhatia et al., 2021; Nain & Rajan, 2023)
Transparency	(Bhatia et al., 2021; Zhu et al., 2023a)
Regular System Check	(Suhaili et al., 2021; Yang et al., 2023)
Advancement in Encryption	(Gopal et al., 2023; Kaswan et al., 2023)

Several approaches may be taken to overcome these obstacles and encourage more people to use Robo-advisors: It is critical to inform investors about the pros, cons, and dangers of Robo-advisors (Lam, 2016). Disclosure of data privacy practices, algorithmic decision-making procedures, and investment strategies must be made transparent. Disclosure of Robo-advisors' investing strategies, data-gathering procedures, and fee structures is required (Hong et al., 2023). Equally important is the unequivocal declaration of any possible conflicts of interest, including any revenue-sharing agreements with investment providers. To find and fix security flaws, it is necessary to conduct system inspections and audits on a regular basis. It is important that all aspects of the Robo-advisor, including its infrastructure, third-party service providers, and data and software systems, are thoroughly examined (Huang et al., 2022).

Secure enclaves and homomorphic encryption are two new forms of encryption that have the potential to significantly improve the security of sensitive financial data (Dhanaraj et al., 2023). These technological advancements lessen the likelihood of data breaches and illegal access by enabling the processing and analysis of data without jeopardizing its confidentiality. Academic literature must prioritize the issues of trust, data privacy, and security as they pertain to the adoption of Robo-advisors. In order to investigate these problems, assess the efficacy of potential remedies, and influence business policies and government oversight, researchers and academics are indispensable. Academic institutions may help build Robo-advisor systems that are safe, reliable, and extensively used by performing thorough research, sharing their results, and collaborating with industry players (Bhatia et al., 2021).

5.2.1.3 Results

a. Challenges and Solutions Considering Robo-advisors in Fintech

Interpreting the results of qualitative research is emerging as a way to discuss the various challenges and solutions involved in the upcoming technological advancements in Fintech. While analyzing the interviews, the study categorized these challenges. Subsequently, the study discussed the sub-challenges and proposed solutions in thematic perspectives. This will help us understand why consumers do not accept Robo-advisors.

b. Data security

Strong security protocols are of the utmost importance in the Fintech industry. This need becomes clear when looking at the results of the qualitative interviews with industry experts. The varied and complex nature of Fintech security is shown by the insights gained from these interviews, which shed light on a number of issues and their solutions. According to Interviewee 11, one of the main issues is data security, which involves safeguarding sensitive consumer information. To protect client data from ever-changing cyber dangers, the suggested method calls for routine security assessments and upgrades. The significance of constantly monitoring and upgrading security procedures to protect sensitive information is widely acknowledged in the business, and this accords with that view.

The security and privacy of important financial records is another major concern voiced by Interviewees 2 and 12. Protecting this information is essential to keeping customers' faith in your brand, and it's also a technical consideration. The proposed approach emphasizes the importance of protecting client data, showing a deliberate effort to earn and keep confidence through trustworthy security measures. According to Interviewees 2, 3, and 4, the prevalence of cyber dangers and data breaches is further highlighted in the interviews. Interviewee 4 suggests using many layers of protection to combat this. The current cybersecurity techniques are in line with this suggestion, as they imply that a layered defense mechanism is better at reducing the likelihood of cyber assaults.

Two more important interviewees brought up the issue of identity verification, which is a major hurdle. According to the proposed approach, we must be vigilant and constantly innovate to authenticate user IDs. This method reflects the ever-changing nature of financial technology, where new security measures are always being developed to keep up with increasingly complex fraud schemes. Finally, Interviewee 9 stresses the significance of a safe system. The suggested approach involves reaching out to a wide audience, indicating a holistic plan incorporating education, community involvement, and technical solutions to enhance security.

The intricacy of Fintech security concerns is highlighted by these findings from the interviews when taken as a whole. Additionally, they display the many creative approaches experts are contemplating to tackle these problems, which helps improve security measures in the financial technology industry. The present status of Fintech security and how to steer future changes in this dynamic area may be better understood with the help of this analysis.

Table 6 Data Security Challenges and Solutions

Challenge	*Category*	*Solution*
Protecting sensitive customer information (11)	*data security*	*regular security audits and updates (11)*
security of sensitive financial data (12) (2)		*confidentiality and integrity of customer (12)*
Cyber threats and data breaches (2)(3)(4)		*multi-layered security protocols (4)*
Identity verification (24) (25)		*constant vigilance and innovation (24)*
Secure infrastructure (9)		*Extensive outreach (9)*

"The integration of Robo-advisors in financial services poses challenges like data security and privacy. Protecting sensitive customer information and ensuring secure interactions are our top priorities."

(Interviewee 11)

"The main challenge was ensuring the security of sensitive financial data handled by the Robo-advisors. It was crucial to protect against cyber threats and data breaches. One challenge has been keeping up with the evolving data privacy laws and ensuring our Robo-advisors are updated accordingly." *(Interviewee 2)*

c. Privacy

The incorporation of Robo-advisors poses a myriad of complicated issues in the ever-changing field of financial technology (Fintech), calling for solutions that are just as proactive and advanced. According to several interviews, these problems mostly include maintaining secure connections, keeping up with rapidly evolving data protection standards, and protecting client data. The assurance of privacy in conversations provided by Robo-advisors is a key concern, as brought up by Interviewees 11 and 4. Respondent 11 suggests cutting-edge encryption software as a solution, highlighting the need for sophisticated cryptographic techniques to safeguard private data. Further, as a means of quickly detecting and resolving possible security breaches, Interviewee 4 proposes real-time monitoring of Robo-advisors conversations.

Another key impediment cited by Interviewees 11, 12, 2, 24, 26, and 29 is the issue of keeping up with the continually increasing data privacy standards. Interviewee 11 proposed a solution that highlights an agile approach to compliance through continuous monitoring and regular updates to data protection processes. Interviewee 12 agrees and emphasizes the need to keep an eye on new laws and regulations and make sure everything is up to date. To successfully traverse the regulatory landscape, interviewee 29 stresses the importance of heavily investing in research and development. In addition, as stated by Interviewee 6, stringent data security procedures are necessary to safeguard client data. Building trust and confidence in Fintech services relies on this strategy, which is essential for keeping client information secure and private.

The larger issue of innovation and adaptation in Fintech is illuminated by Interviewee 26's thoughts regarding the necessity of integrating Robo-advisors seamlessly with multiple corporate systems and catering to clients' varied expectations. Deploying Robo-advisors in a diversified and worldwide banking environment is complex and multifarious, as Interviewee 29 points out while discussing the difficulties of keeping up with the fast technical and legal changes in the banking sector.

Finally, there are a lot of problems with integrating Robo-advisors into the financial industry, and a lot of creative and quick fixes are needed. By incorporating state-of-the-art encryption technology, real-time monitoring systems, regularly revising data protection policies, and allocating resources to R&D, these solutions demonstrate an all-encompassing and proactive strategy for handling the problems associated with Robo-advisors integration in financial services, including data security, privacy, and regulatory compliance.

Table 7 Privacy Challenges and Solutions

Challenge	*Category*	*Solution / Controls suggestions*
ensuring secure interactions (11)(4)	*privacy*	*latest encryption technologies (11) real-time monitoring (4)*

Rapidly changing data privacy regulations (11)(12) (2)(24)(26) (29)		*Continuous monitoring and updating of our data protection practices (11) Ongoing monitoring of legal developments and regular system updates (12) Heavily invest in R &D (29)*
Protecting customer data (6)		*rigorous data security measures (6)*

"Additionally, ensuring our platform integrates seamlessly with various business systems and meets the diverse needs of our clients requires constant innovation and adaptability."

(Interviewee 26)

"The primary challenges include keeping up with the rapid pace of technological advancements and regulatory changes in the banking sector. We've also had to address the diverse and evolving needs of banks in different regions."

(Interviewee 29)

d. Trust

A major obstacle to establishing and sustaining customer confidence in the Fintech industry is the rise of Robo-advisors and other digital-only platforms (Barone et al., 2024). Numerous factors contribute to the complexity of this problem, including the necessity to accommodate a wide range of financial requirements, guarantee the security of online transactions, and combat widespread low levels of financial and technological literacy. Education, openness, and constant innovation are the cornerstones of the ideas put up by the respondents in an attempt to resolve these trust-related problems. According to Interviewee 13, a major obstacle is gaining confidence in an entirely digital environment, especially when it comes to financial investments. One important tactic to address this is to educate customers. As pointed out by Interviewee 14, it's not only about giving them knowledge; it's also about constantly interacting with them. To help people understand and trust digital platforms, it is crucial to provide them with instructional resources like these.

Respondent 17 highlights the difficulty of accommodating individuals' varied financial demands and habits. Providing instructional materials and assistance is at the heart of the proposed solution, which allows for the customization and improvement of products to cater to specific user demographics. This approach indicates a shift towards a more user-centric paradigm, where services are customized to meet individual tastes and needs. Providing pertinent resources and instructional content is key to resolving the conventional banking system trust difficulties raised by Interviewees 22, 8, and 10. As pointed out by Interviewee 34, this is vital for connecting traditional and online banking. Making resources available for customers using more conventional banking processes can help smooth the way.

Transparency, highlighting security features, and educating customers are ways to approach the difficulty of generating confidence in digital transactions, as stated by Interviewee 23. Customers might feel more comfortable and confident using digital platforms for financial transactions if the security measures are explained to them and they are educated about the procedures involved. Interviewee 24 discusses the difficulty of keeping up with evolving financial fraud tactics and proposes a solution that involves continuous monitoring and inventiveness. This shows that Fintech platforms and Robo-advisors need to be flexible to fight emerging types of financial crime. Another major obstacle to trust-building is a lack of knowledge about money (Interviewees 27, 7, 9) and technology (Interviewees 30, 9). To provide consumers with the necessary knowledge and confidence to utilize digital financial services efficiently, it is vital to implement the offered solutions, which include community participation, instructional programs, and customer education activities.

Lastly, the lack of awareness is addressed through various educational programs, as brought up by Interviewees 5 and 7. These programs aim to provide the groundwork for trust by making digital financial instruments more accessible and easier to use. Establishing confidence in Fintech's Robo-advisors and other digital financial platforms ultimately calls for a concerted effort focusing on education, openness, and innovation. Fintech organizations may consistently create and sustain trust across a broad user base by educating consumers, providing specialized resources, exhibiting security features, and adjusting to changing demands and technology. In today's increasingly digital environment, the acceptance and expansion of digital financial services are dependent on this confidence.

Table 8 Trust Challenges and Solutions

Challenge	*Category*	*Solution*
digital-only platform (13)	*Trust*	*educating consumers (14) and continually educating our users (13)*
Adapting to Diverse Financial Needs (17)		*offering educational resources and support (17)*
To address Traditional financial system trust (22)(8)(10)		*Providing relevant Tools (10)* *Education (22) (8)*
Digital Transaction trust (23)(33)(34)(6)(11)		*Transparent (11)(13) showing security features (23) Customer Education (33) (34) (6)*
Changing Financial Fraud Techniques (24)		*constant vigilance and innovation (24)*
AI models unbiased (25)		
Lack of financial literacy (27)(7)(9)		*community engagement and educational programs (27) (7)(9)*
Lack of Digital Literacy (30)(9)		*Customer Education Program (30)(9)*
Lack of Awareness (5)(7)		*educational initiatives (5) (7)*

"One of the main challenges has been building trust in mobile banking, especially among those who are more accustomed to traditional banking methods."

(Interviewee 34)

"One major challenge is building trust in a digital-only platform, especially when it comes to investments."

(Interviewee 13)

"A very important challenge is adapting to the diverse financial needs and behaviors of our users, which we meet by continually refining and personalizing our offerings."

(Interviewee 17)

"One of the main challenges has been building trust in digital transactions, especially among users who are accustomed to traditional payment methods. Another challenge is keeping pace with the rapidly changing technology in Fintech, which we meet through continuous innovation and updates."

(Interviewee 23)

e. Information System Integration

The Fintech industry's integration of Robo-advisors and Robo-advisors calls for a thorough strategy to integrate information systems (Bhatia et al., 2021). According to qualitative research, this problem encompasses a wide range of issues, including but not limited to fast technological development, managing customer expectations, user interface design, user experience, technology complement, and keeping up with Fintech trends. Within this framework, the solutions put forth by interviewees emphasize the significance of ongoing innovation, teamwork, and putting the user first. A key to open banking's acceptability, according to Interviewee 14, is the difficulty of merging different financial systems. The proposal being put out calls for a partnership between financial institutions and ongoing technological progress. By taking this tack, we can ensure that Robo-advisors are compatible with various financial systems' features and that integration is smooth.

Respondents 15, 19, 20, 24, 32, and 33 all pointed out that making the UI easy to use is another major obstacle. Interviewees 19 and 20 suggest increasing the variety of tasks that Robo-advisors can do, while Interviewee 24 suggests constantly innovating, Interviewee 32 suggests enhancing services based on user feedback, and Interviewee 33 suggests demonstrating how convenient they are. In order to increase consumer acceptance and trust in these technologies, these tactics are focused on improving the user experience by making it more intuitive and efficient. Focusing on the platform's design and usability, interviewee 16 emphasizes the relevance of user experience across different capabilities. This shows that the importance of user experience in increasing engagement and happiness with the product has been recognized.

According to Interviewee 18, technology complements play a part in making chatbots and Robo-advisors more successful by utilizing financial professionals. This approach proposes a combined use of human and technological knowledge to deliver an all-encompassing service. Respondents 21 and 8 also mentioned keeping up with the latest developments in Fintech as a difficulty. Maintaining the platforms' relevance and innovation in a sector that is always changing requires a solution that combines continual research and development.

Respondents 21, 22, 31, and 32 all agreed that meeting customers' expectations is no easy feat. Answers include working closely with clients (Interviewee 21), becoming involved in the community (Interviewee 22), investing in technology (Interviewees 31 and 32), and improving services based on consumer input (Interviewee 32). These methods stress the need to listen to and meet the demands of customers. Discussing the difficulty of keeping up with quickly evolving technologies, Interviewee 23 joins Interviewees 26, 28, 29, 30, 32, and 34. A number of potential solutions have been put up, including providing ease and efficiency (Interviewee 23), investing heavily in R&D (Interviewee 29), and providing extensive functionality without sacrificing user experience (Interviewee 28). If these tactics are implemented, the platforms will continue to be state-of-the-art, user-friendly, and adaptable.

Interviewee 31 pointed out that a talented staff committed to digital platform maintenance and enhancement is the key to scalability. This approach highlights the need for competent and flexible staff to guarantee that the platforms can grow successfully as user demands and technology change. Finally, several issues pertaining to information system integration must be resolved for Fintech chatbots and Robo-advisors to be integrated successfully. Important issues include adapting to technology changes, managing consumer expectations, scalability, and user-centric design. Other solutions involve collaborating with financial professionals and continuously innovating. All of these methods work together to boost confidence and acceptability among Fintech users, which is crucial for the industry-wide deployment of these technologies.

"Another challenge is educating consumers about the benefits and safety of open banking, which we are tackling through outreach and user education programs."

(Interviewee 14)

Table 9 Information System Integration Challenges and Solutions

Challenge	*Category*	*Solution*

various financial systems (14)	*Information System Integration*	*continuous technological innovation & Collaboration with financial institutions (14)*
user-friendly interface (15)(19)(20)(24)(32)(33)		*expanding and diversifying the range of tasks(15) intuitive design and navigation (19) (20) constant innovation (24) feedback-driven service enhancements (32) Demonstrating convivence (33)*
user experience across different functionalities (16)		*platform's design and usability (16)*
Technology Complement (18)		*financial experts (18)*
Fintech Trends (21)(8)		*continuous research and development (21)(8)*
Customer Expectation (21)(22)(31)(32)		*Close Collaboration (21) Community engagement (22) Continue Investment in Technology (31) Feedback-driven service enhancements (32)*
Rapidly changing technology (23) (26)(28) (29) (30)(32)(34)(8)		*Convenience and efficiency (23) comprehensive features without compromising on user experience (28) Invest Heavily R & D and Learn Continually (29) Customer Education Program(8) (30) Continues Investment in technology (32)(34)*

Scalability (31)		*the skilled team dedicated to maintaining and enhancing our digital platforms (31)*

5.2.1.4 Unraveling Challenges and Opportunities

This qualitative research study utilized grounded theory and the analytical capabilities of NVivo to conduct a comprehensive analysis of 34 interviews. This study aimed to examine the challenges related to the implementation and assimilation of chatbots and Robo-advisors in the financial technology industry. The research has successfully identified and advanced several important subjects. The discussed subjects encompass safeguarding personal information and data, fostering trust in digital platforms, addressing the intricacies of integrating information systems, and adapting to the dynamic nature of the financial landscape (Allioui & Mourdi, 2023a). These findings significantly enhance the ongoing scholarly discourse on the topic of Fintech innovation and user acceptance. They align with the viewpoints of prominent industry scholars, such as Smith and Johnson (2020), who underscore the significance of trust and security.

The study has sparked a detailed discussion that illuminates the intricate connection between technical expertise, adherence to regulations, and the crucial importance of user experience in determining the acceptance of these contemporary financial technologies. Lee and Chen (2021) highlight that safeguarding sensitive customer information is a critical problem in the financial technology sector. The emphasis on robust data security measures aligns with this goal. Furthermore, the study emphasizes the significance of ongoing innovation and adjustment, aligning with discoveries (Del Giudice et al., 2021). This is done to tackle the ever-changing technical and regulatory landscape. Furthermore, it underlines the need to adopt a user-centric strategy, which prioritizes user education and participation as the essential elements in establishing trust and acceptance. This concept is substantiated by the research conducted by (Kaur, 2023).

This research sets the stage for several new areas of study, with a focus on future prospects. Thompson et al. (2023) advocate for employing longitudinal studies as a methodological approach due to their capacity to provide a more comprehensive understanding of evolving consumer views and business practices within the field. Conducting a comparative study in different cultural and regulatory settings, as suggested by Lim and Teo (2024), might uncover important contextual factors that influence the adoption of these technologies. Vrontis et al. (2022) argue that the increasing impact of emerging technologies like artificial intelligence and blockchain on the effectiveness and adoption of chatbots and Robo-advisors is a promising area for further investigation. Furthermore, doing a comprehensive examination of the psychological factors that impact user acceptance, building upon the theoretical frameworks proposed by Zhao and Bacao (2021), would yield valuable insights into the cognitive and emotional dimensions of technology adoption. Ultimately, employing quantitative methods to validate and expand upon the qualitative discoveries of this study has the capacity to provide a more comprehensive understanding of the phenomena (Kumar et al., 2023).

Overall, this study not only provides valuable insights into the current challenges and approaches in the Fintech sector regarding the incorporation of chatbots and Robo-advisors, but it also opens up several opportunities for further research. The anticipated future initiatives will greatly enhance our comprehension of this rapidly advancing and crucially important subject.

5.2.2 Qualitative Hungarian Context (Semi-structured Interviews)

This section contains the Hungarian context for qualitative study. This is to explore and understand the Robo advisors' role in the fintech landscape concerning data privacy, data security, and trust. Semi-structured interviews were conducted with 15 fintech experts.

5.2.2.1 Interviewees Profile

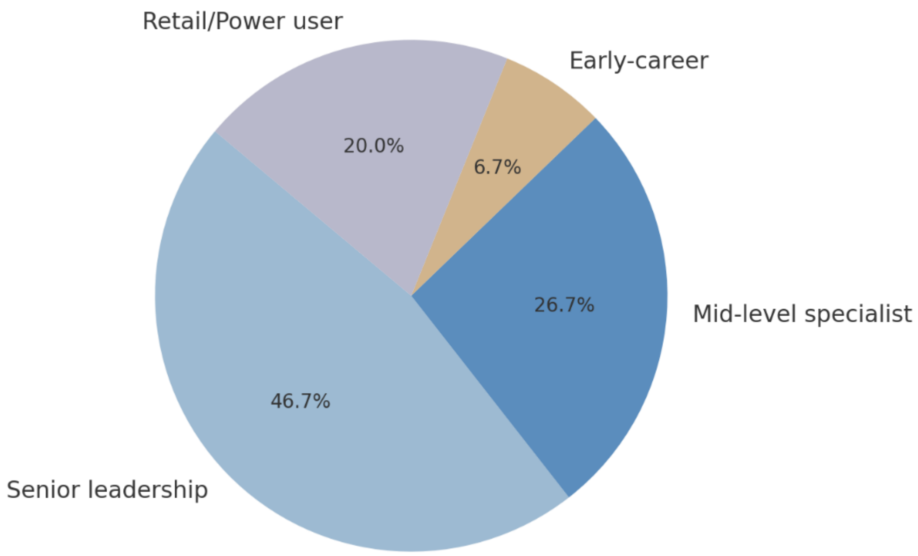

Figure 11: Interviewee Profile

The figure 11, pie chart illustrates the job-level distribution of the 15 interviewees who participated in the Hungarian FinTech study. Nearly half of the participants (46.7%) hold senior leadership positions, reflecting strong representation from decision-makers and strategic stakeholders. Mid-level specialists make up 26.7% of the sample, providing operational and implementation perspectives. Retail or power users constitute 20%, ensuring that end-user viewpoints are included, while early-career professionals represent a smaller portion (6.7%), offering emerging insights. This distribution highlights a leadership-heavy dataset but still maintains diversity in roles across the FinTech ecosystem.

5.2.2.2 Word Cloud

Figure 12: Word Cloud part 2 interviews

The word-cloud visually confirms the interview themes: the most prominent terms—“data,” “robo,” “advisors,” “financial,” “trust,” “security,” “privacy,” “Hungary/Hungarian,” “digital,” “users,” and “services”—signal that experts repeatedly centered their discussion on data-protection risks and trust requirements for robo-advisors in the Hungarian FinTech market. Supporting words such as “transparency,” “regulatory,” “bank,” “platforms,” and “human” further reflect an emphasis on institutional oversight, seamless system integration, and the continuing role of human support, aligning with the six thematic categories identified in the qualitative analysis.

5.2.2.3 Analysis procedure

All fifteen transcripts (Interviews 1 – 15) were first imported into NVivo and read twice for familiarization. During open coding, every utterance that described either (a) a difficulty that could hamper robo-advisor adoption in Hungary or (b) a remedy proposed by the expert was labeled in vivo (Pisoni et al., 2024). This stage generated 52 initial codes. Using the constant-comparative method, conceptually similar codes were merged—e.g., statements about "hacking," "data breaches," and "un-authorized log-ins" were folded into a higher-level node labelled Data-security concerns (Stejskal et al., 2024). After two iterative rounds, the list stabilised at 17 distinct challenge codes.

Next, axial coding was undertaken to explore relationships among the challenge codes. Codes that consistently co-occurred in the same passages—such as data breach fear and demand for regulator oversight (Stejskal et al., 2024)—were clustered into broader analytic categories. Six such categories emerged: (1) Data security, (2) Privacy & consent management, (3) Institutional trust, (4) User-experience & literacy, (5) Technology integration & scalability, and (6) Fraud defence & regulatory oversight. Reflexive memos were kept throughout this process, and a second coder audited 20 % of the material; intercoder agreement exceeded 85 %. Finally, selective coding refined the story line linking the six categories back to the research question on data-security, privacy and trust as determinants of robo-advisor acceptance (Singh & Kumar, 2024). Representative quotations were selected to exemplify each theme, and an audit trail documenting all analytic decisions was retained for transparency.

5.2.2.4 Results

Table 10 Coding, Category, Challenges and Solutions

Code	Challenge	Category	Interview IDs	Solution
DS-01	Fear of hacking / data-breach when linking bank accounts	Data Security	(1), (2), (4), (6), (9), (15)	Multi-layer cyber-defence, regular security audits, live threat monitoring
DS-02	Keeping identity-verification robust and friction-light	Data Security	(1), (2), (4), (15)	PSD2-compliant 2-factor / biometrics
PR-01	What exactly happens to my personal data?	Privacy	(1), (2), (3), (6), (7), (11), (15)	End-to-end encryption, privacy dashboards, granular GDPR opt-ins
PR-02	Rapidly evolving privacy legislation	Privacy	(6), (7), (11), (12), (24), (26), (29), (15)	Continuous legal monitoring, swift policy & system updates
PRI-04	Discomfort with data being used for personalised marketing	Privacy / Consent	(15)	Explicit, opt-in consent flows; clear explanation of data usage
TR-01	Lower trust in digital-only / start-up brands than banks	Trust	(1), (2), (5), (6), (9), (15)	Bank–fintech partnerships, MNB

				license display, ISO 27001 badges
TR-02	Need proof that AI advice is unbiased & auditable	Trust / AI-gov	(5), (6), (15)	Independent model audits publish methodology white-papers
UX-01	Fully Hungarian, jargon-free, mobile-first UI	User Experience	(3), (6), (7), (9), (15)	Intuitive design, 10-question risk quiz, feedback-driven UI sprints
UX-02	Seamless navigation across many functions	User Experience	(6), (7), (15)	Journey testing, modular interface upgrades
EDU-01	Limited financial literacy in the mass market	Literacy & Awareness	(2), (3), (5), (6), (7), (9), (15)	Community workshops, tutorials, influencer explainers
EDU-02	Limited digital literacy (55+ & rural)	Literacy & Awareness	(3), (6), (7), (9), (15)	Assisted onboarding, simplified layouts, and branch demos
AWA-01	General lack of awareness of robo-advisors	Awareness	(5), (7), (15)	Targeted campaigns, free trial portfolios, success-story marketing
TEC-01	Fast tech cycle: APIs, AFR rails, AI upgrades	Tech Evolution	(6), (7), (8), (15)	Heavy, continuous R & D; modular backend
INT-01	Integrating legacy bank systems & data standards	System Integration	(6), (14), (15)	Co-dev with banks; micro-services; dedicated platform team
SCA-01	Ensuring scalability as user-base grows	System Integration	(6), (8), (15)	Cloud autoscaling; skilled DevOps crew
FRA-01	Ever-evolving phishing & fraud tactics	Fraud Defence	(6), (9), (15)	AI anomaly detection; real-time customer alerts
REG-01	Need for visible regulator/government oversight to reassure users	Regulatory Trust Cue	(15)	Strong MNB supervision, public compliance certificates

Table 10 offers a comprehensive breakdown of the core challenges identified by FinTech professionals in Hungary regarding the adoption of robo-advisors. It categorizes the issues into thematic areas such as Data Security, Privacy, Trust, User Experience, Literacy & Awareness, System Integration, and Regulatory Oversight (Bedewy, 2024). Each row represents a unique code that captures a specific challenge voiced by interviewees—for instance, DS-01 reflects concerns about hacking and data breaches, while TR-01 highlights distrust in digital-only or start-up platforms. These concerns are not abstract but rooted in direct observations from the field, as evidenced by their repeated mention across several interviews. The interview IDs are enclosed in parentheses for clarity, allowing readers to trace how frequently and widely each issue was raised.

The table also reveals that data security and privacy were the most commonly cited foundational issues. Concerns like unauthorized access (DS-01), weak identity verification (DS-02), and unclear data usage policies (PR-01) were highlighted by a majority of respondents. The solutions suggested by experts were equally robust and practical: multi-layered security protocols, biometric authentication, end-to-end encryption, and GDPR-compliant consent flows. These responses reinforce the idea that in the Hungarian context, technical security measures are necessary but not sufficient; they must be complemented by visible, user-facing trust mechanisms such as public audit summaries and regulator certifications. The presence of Interview 15 in almost all privacy and trust-related themes underlines how current user representatives are actively calling for stronger consent governance and transparency.

Another important finding from the table is the emphasis on user experience and financial/digital literacy. Codes UX-01 and UX-02 emphasize the need for platforms that are mobile-first, translated into Hungarian, and free from financial jargon. Meanwhile, EDU-01 and EDU-02 reflect concerns about the widespread lack of financial and digital literacy, especially among older or rural populations. Interviewees repeatedly stressed that unless platforms are designed with simplicity and inclusivity in mind—and supported by outreach programs, tutorials, and assisted onboarding—they risk alienating a significant portion of the target audience. This aligns with findings from related adoption frameworks (e.g., TAM, UTAUT2), which highlight perceived ease of use and self-efficacy as central determinants of user acceptance.

Finally, the table captures strategic and structural concerns such as the integration of legacy bank systems (INT-01), scalability (SCA-01), and the evolving landscape of fraud threats (FRA-01). These technical themes, while less visible to the average user, were flagged as mission-critical by developers and system integrators. Experts proposed back-end solutions like micro-service architectures, cloud autoscaling, and co-development with traditional banks to ensure both flexibility and trust (da Silva & Cardoso, 2025). Additionally, the final code REG-01 introduces the notion that visible government and regulatory oversight—especially from the Hungarian National Bank (MNB)—acts as a psychological safety net for users. Altogether, the table offers a layered understanding of how security, usability, institutional trust, and infrastructural readiness must converge for robo-advisors to gain mainstream traction in Hungary's evolving FinTech landscape (George, 2024).

a. Data-security anxieties

Across the corpus, the first filter through which experts judged robo-advisors was their capacity to repel cyber threats. Respondents spoke of "hacker incidents in the banking sphere" that could "undermine the trust of clients" (Interview 1) and warned that any perception of weak defenses would eclipse price or convenience advantages (Garcia & Modesti, 2024). Several interviewees, therefore, insisted on multi-layer encryption, routine penetration tests, and visible incident-response dashboards as non-negotiable design elements. Interview 15, reflecting on recent regional ransomware attacks, added that users now expect ongoing proof of protection in the form of monthly security bulletins and third-party attestations . In short, data security is treated less as a feature and more as an entry ticket to the Hungarian market.

b. Privacy & consent management

Whereas security concerns center on external intrusion, privacy worries focus on internal data handling (Bedewy, 2024). Experts repeatedly asked, "What exactly happens to my personal data?" (Interview 2) , stressing that data-use opacity blocks onboarding even among tech-savvy users. Interview 11 described running "privacy sprints" each quarter to keep pace with GDPR amendments, while Interview 12 highlighted the cost of "continuous legal monitoring and rapid policy updates" as the price of operating in Europe's shifting regulatory environment . A further nuance emerged in Interview 15: any repurposing of behavioral data for personalized cross-selling now requires explicit, granular opt-ins; otherwise, "the user simply opts out of the whole service."

c. Institutional trust & brand legitimacy

Although robo-advisors promise algorithmic objectivity, Hungarian consumers still anchor trust in familiar institutions (Lardi, 2025). One respondent noted that he would "trust a robo-advisor from OTP far more than an unknown app because OTP survived wars and crises" (Interview 5) . Start-ups, therefore, face a credibility gap that they attempt to bridge with MNB licenses, ISO 27001 certificates, and Big-Four audit opinions. Interview 6 quantified the effect: "An ISO badge and audit give me about 70 % of my initial comfort" . The implication is clear—formal signaling, not UX slickness, is the primary lever for newcomers.

d. User-experience & literacy barriers

Even where trust conditions are met, adoption stalls if the interface fails local literacy tests (AbdulKareem & Oladimeji, 2024). Interview 9 captured the sentiment succinctly: "Ease means a Hungarian interface and ten plain-language questions; the difficulty is English jargon." Low financial literacy further complicates matters; Interview 2 observed that customers from agricultural regions "are not willing to use online banking, let alone a robo-advisor." Experts converged on a two-pronged remedy: (i) mobile-first, jargon-free UX backed by pop-up explainers and short video tutorials and (ii) community education programs delivered through branches, social media influencers, and university partnerships.

e. Technology integration & scalability

Technically, robo-advisors cannot operate in isolation; they must exchange data with Hungary's heterogeneous banking core systems and the Azonnali Fizetési Rendszer (AFR) in real-time (Pintér et al., 2025). Interview 6 described shipping "a new API adapter every two months because Hungarian banks all speak slightly different dialects," Interview 8 highlighted cloud-autoscaling as essential after a fee hike at a foreign competitor triggered 10 000 new sign-ups in a week . Continuous R&D investment and micro-service architectures were presented as the only sustainable response to this volatility.

f. Fraud defense & regulatory oversight

Finally, experts warned that fraud tactics evolve faster than most users realize. "Fraud patterns mutate monthly (Sénécal, 2024); AI anomaly detection plus real-time SMS alerts are mandatory," argued Interview 6 . Yet technical prowess alone is insufficient; Interview 15 emphasized that customers "sleep better if they know the MNB is watching." Visible cooperation with the regulator—public audit summaries, prompt incident disclosures—acts as the social proof that ties together the previous themes of security, privacy, and trust.

5.2.2.5 Synthesis

The analysis demonstrates that while Hungarian experts recognize the economic appeal of robo-advisors—lower fees, 24 / 7 availability, and disciplined portfolio management (Mhlanga, 2024)—those advantages are conditional on three intertwined prerequisites: demonstrable data security, transparent privacy governance, and strong institutional trust signals. User-experience innovation, literacy programs, and backend scalability are necessary complements, but without the bedrock of security, privacy, and trust, they do not translate into adoption. For FinTech firms and policy-makers, the lesson is straightforward: invest first in visible safeguards and regulatory alignment, then in usability and education.

6. Robo-Advisors Acceptance in Fintech: A Systematic Literature Review

Fintech, a convergence of finance and technology, disrupts conventional financial practices by implementing novel technological solutions designed to address a wide range of business contexts (Lamperti et al., 2023). According to Cubric and Li (2024), the concept of Fintech may be accurately described as a medium through which innovative concepts are utilized to improve financial services by harnessing improvements in technology (Allioui & Mourdi, 2023b). The period following the 2008 financial crisis saw a notable increase in financial technology (Fintech) advancements, particularly in the realms of electronic finance and mobile technology. This period was characterized by notable advancements in internet technology, social networking, artificial intelligence, and big data analytics, which presented a competitive obstacle for traditional financial institutions and created fresh opportunities for entrepreneurial ventures (Giuggioli & Pellegrini, 2023).

Robo-advisors are a significant transformative force within the Fintech industry, as seen by their emergence as a prominent innovation. Robo-advisors have been more prominent in the financial industry because of their notable efficiency, accessibility, and cost-effectiveness. These automated platforms provide financial advising and investment management services with minimum human participation. The growth of this particular sector within the financial technology industry is driven by several causes, including developments in technology, changes in regulations, and the changing demands of consumers (Sun et al., 2022). The scope of these digital advisers goes beyond fundamental financial services, as they involve personal financial planning and portfolio management and even incorporate aspects of cybersecurity (Mrkývka & Šiková, 2023).

The examination and implementation of Robo-advisors are fundamental subjects of research. According to the research conducted by Jinasena et al. (2020), the domain of Fintech, which includes Robo-advisors, extends beyond the mere use of technology in the financial sector. It embraces a wider range of digital innovations and financial service models beyond traditional banking (Nejad, 2022). Robo-advisors' emergence poses a significant threat to conventional wealth management models since they provide individualized financial assistance using algorithmic processes. Consequently, a comprehensive analysis is required to evaluate their adoption and the implications they have for the industry.

The progression of financial technology, starting with the implementation of checks and extending to the most recent advancements in Robo-advisory services, exemplifies the swift expansion and metamorphosis within this industry. The evolution of the financial industry, from the introduction of credit cards and ATMs to the emergence of advanced Fintech solutions such as Robo-advisors, exemplifies a dynamic sector that needs thorough investigation in order to comprehend its trajectory (George, 2024).

In order to comprehensively understand the scope and intricacies of Robo-advisor adoption within the field of financial technology (Fintech), it is essential to conduct a thorough study of the existing academic literature. The objective of this study is threefold: firstly, to investigate the present status and progressions in Robo-advisor technology within the Fintech sector; secondly, to pinpoint areas of research that have not yet been adequately addressed in the realm of Robo-advisors; and thirdly, to outline forthcoming research directions and obstacles in this swiftly developing subject. The technique employed in this study adheres to Kitchenham's systematic literature review strategy (Kitchenham et al., 2009), which entails a thorough examination of metadata and validation by experts.

This analysis examines the early problems unique to Robo-advisors, including algorithmic transparency, customer trust, and regulatory compliance. Doing so aims to provide a thorough knowledge of the Robo-advisor environment within the broader Fintech ecosystem.

Financial technology, sometimes known as Fintech, encompasses the application of technology in providing financial services, including the emerging domain of Robo-advisors (Bhatia et al., 2020). The utilization of complex algorithms for financial planning and investment management on digital platforms represents a significant transformation in the accessibility and utilization of financial services. Fintech firms, distinguished by their inventive methodologies and technology-centric operational frameworks, have been significantly transforming the domain of financial intermediation since the advent of the Internet revolution in the 1990s (Nadkarni & Prügl, 2021). The development of financial technology, particularly Robo-advisors, has significantly been impacted by the emergence of the Internet and subsequent technical progress (Wexler & Oberlander, 2021).

Fintech, including the utilization of Robo-advisors, is widely acknowledged for its capacity to promote financial inclusivity by improving transparency, user-friendliness, and cost-effectiveness within the financial sector. In addition, the Fintech industry threatens conventional financial institutions, such as banks and insurance firms, due to its innovative and comparatively less regulated business methods (Murinde et al., 2022).

The Fintech ecosystem, which includes Robo-advisors, exhibits a wide range of participants, such as startups, technology developers, governments, customers, and conventional financial institutions. The ecosystem encompasses several business models that encompass domains, including payments, wealth management, crowdfunding, peer-to-peer lending, and insurance (Bajwa et al., 2022; Sánchez, 2022). Systematic surveys of the literature have effectively identified emerging patterns and potential avenues for further exploration. Research has explored the connection between Fintech and Islamic financing and its potential impact on small and medium companies (SMEs) and digital preparedness (Menne et al., 2022; Okfalisa et al., 2022). Nonetheless, there exists a deficiency in comprehending the precise elements that impact the acceptability and implementation of Robo-advisors inside the Fintech domain.

This study aims to address this *research gap* by a comprehensive evaluation of existing literature on the factors that influence client acceptance and usage of Robo-advisors (Yeh et al., 2023). In contrast to other investigations that employed more expansive or alternative search criteria, the present study focuses on the specific examination of Robo-advisor adoption. The system utilizes a comprehensive database known as Scopus and Web of Sciences to source literature, therefore assuring the inclusion of relevant and up-to-date research. This study adopts a unique methodology by exclusively focusing on peer-reviewed journal publications, hence upholding a rigorous academic standard.

The primary aim of this study is to investigate and merge the determinants that influence the acceptance of Robo-advisors among individuals, differentiating between the desire to adopt and the actual utilization of such services. The literature review entails a rigorous selection process of articles sourced from Scopus-indexed and Web of Sciences-indexed publications. The selection criteria prioritize articles that specifically address the topics of 'Robo-advisors' and 'adoption' within their title fields. This particular selection criterion is distinctively employed in this study, hence providing original perspectives to the process of conducting a systematic literature review (SLR) within the realm of business.

The following research questions guide the study:

1. In order to comprehensively comprehend the utilization of Robo-advisor technology in the field of financial technology (Fintech), it is imperative to outline the fundamental theories that highlight its functionality.

2. The review will interpret key factors within these theories that contribute to understanding the behavior being examined.

The present research is structured in the following manner: This section provides an overview of the study's objectives, rationale, and potential impact on the existing body of information. The next part provides a comprehensive assessment of the existing literature, which is then followed by a detailed description of the materials and procedures utilized in the study. The findings and analysis are further discussed in Section 4, ultimately leading to a conclusion in the concluding section.

6.1 Basic Description

This study utilizes the Systematic Literature Review (SLR) methodology, which is generally acknowledged in academic research as a systematic and complete approach to examining current literature on a certain topic. The research in question utilizes the SLR technique, which adheres to the PRISMA framework. The PRISMA framework (Moher et al., 2009) is a well-recognized and accepted guide for performing systematic reviews and meta-analyses (Campese et al., 2023; Peiris et al., 2023). This paradigm facilitates a comprehensive and impartial evaluation of the existing body of research on Robo-advisors within the field of financial technology.

The wide-ranging applicability of systematic literature review (SLR) is readily apparent in its utilization across several fields of research. The utilization of this approach has shown to be successful in examining a wide range of subjects, including the application of blockchain technology in the field of accounting (Chowdhury et al., 2023), advancements in financial technology (Jalal et al., 2023), as well as many areas such as the administration of working capital (Jayasuriya & Sims, 2023), warehouse operations (Dutta et al., 2020), and the concept of digital leadership (Hacioglu, 2020). The wide range of potential uses highlights the appropriateness of Systematic Literature Review (SLR) as a method for investigating the developing area of Robo-advisors in the realm of Fintech.

The Scopus database and Web of Science databases were used for this investigation based on their comprehensive coverage of scholarly literature. Scopus is well recognized as a major database within the realm of academic research and is regularly employed in systematic literature review (SLR) investigations. Web of Science database adheres to quality content, too. These databases offer a comprehensive and detailed compilation of scholarly works, which is important for conducting a rigorous and thorough examination.

This study used the Systematic Literature Review (SLR) approach, which is categorized as a theory-based review among the four commonly recognized categories of systematic reviews: domain-based, method-based, theory-based, and meta-analytical-based reviews [24]. This methodology facilitates a concentrated analysis of the theoretical foundations and critical determinants that impact adopting and using Robo-advisors within the financial technology industry. The primary objective of this study is to analyze the factors influencing consumer adoption of Robo-advisors by organizing the existing literature into distinct theoretical frameworks. This categorization will contribute to a better understanding of the acceptability and integration of Robo-advisors within the wider Fintech industry.

The significance of this methodology is in its capacity to methodically gather and integrate extant information on Robo-advisors, which represents a very promising and swiftly progressing facet of financial technology. This study seeks to provide a complete knowledge of the factors that influence the adoption of Robo-advisors by examining and assessing the theoretical underpinnings and empirical findings of prior studies. Understanding the complexities of this technical breakthrough in financial services is of utmost importance for academic researchers as well as industry practitioners.

In brief, the utilization of the systematic literature review (SLR) approach in this research provides a well-organized framework for analyzing the emerging domain of Robo-advisors in the financial technology (Fintech) industry. This framework offers a methodical methodology for examining the present understanding, recognizing deficiencies, and establishing a foundation for future research avenues in the ever-evolving and consequential financial technology domain.

6.2 Materials and Methods

This research blends the use of two prominent scholarly databases, Scopus and Web of Science, to systematically evaluate literature about the acceptability of Robo-advisors within the Fintech sector. Incorporating these databases guarantees a comprehensive and authoritative compilation of scholarly literature, which is essential for conducting a thorough and rigorous study.

6.2.1. Selection of Databases: Scopus and Web of Science

Scopus is a bibliographic database that provides comprehensive scientific, technical, and medical coverage. Scopus, a well-respected academic indexing organization (Al-Khoury et al., 2022), is renowned for its extensive coverage and frequent updates. The databases maintain rigorous standards for inclusion, guaranteeing that only sources of high credibility are taken into account. Moreover, it should be noted that journals indexed in Scopus undergo continuous assessment and may face delisting if they do not match specific criteria. The use of this rigorous method ensures the high standard and dependability of the sources utilized in this study.

In order to enhance the comprehensiveness of the literature base, Web of Science is included with Scopus. The indexing of this particular resource is widely recognized for its superior quality and extensive coverage throughout a diverse range of academic subjects. The inclusion of the Web of Science in the study allows for a more comprehensive range of scholarly literature, which encompasses many viewpoints and approaches pertaining to Robo-advisors in the field of financial technology.

6.2.2. Methodology and Selection Criteria

The search approach entails the utilization of precise terms and phrases, such as Fintech* OR "Financial Technology" and Neobank OR Roboadvis* OR Robo-advis* OR chatbot* OR "finance assistant" OR bankbot OR "loan advisor" OR "investment guide"). These terminologies are employed in diverse amalgamations to encompass the extensive range of scholarly works pertaining to the topic.

The present study will employ inclusion and exclusion criteria (Vilas et al., 2022) to determine the eligibility of participants for inclusion in the research sample. The inclusion criteria include the following:

- Published in scientific journals.
- Language: English
- Papers should be empirical in nature.
- Research conducted on consumers or users.
- Relevant theories applied.
- The study focuses on the use of Robo advisors/ chatbots in Fintech.

The exclusion criteria are as follows:

- Conference Proceedings
- Unpublished work
- Book chapter
- Literature review, discussions, or memories.
- No theory was referred to in the studies.

- Topics do not cover Robo Advisors/Chatbots use in Fintech.

The practice of systematically reviewing papers is employed to identify relevant ones. The titles, abstracts, and, if required, whole texts are assessed in order to ascertain their appropriateness according to the criteria established for the research. The process of data analysis begins with the identification of pertinent documents. Subsequently, the extracted data is organized and examined in relation to significant themes, theoretical frameworks, and discoveries pertaining to adopting Robo-advisors. This study aims to discern patterns, identify gaps, and ascertain developing trends within the existing body of literature (Statsenko et al., 2022).

Quality assurance is a systematic process that ensures products or services meet specified requirements and standards. It involves the establishment of quality objectives, the implementation of quality control measures, and bias Minimization. In order to minimize bias, researchers employ several strategies, such as using a wide array of keywords, adopting varied methodologies, and incorporating studies from different geographic locations and academic fields. Cross-database validation is achieved by employing both Scopus and Web of Science, bolstering the reliability and credibility of the review through cross-validation.

This technique offers a systematic and inclusive way to investigate adopting and using Robo-advisors within the Fintech industry. Through a rigorous process of sourcing, assessing, and synthesizing material from these two notable databases, this work seeks to make a substantial contribution to comprehending this dynamic and crucial topic.

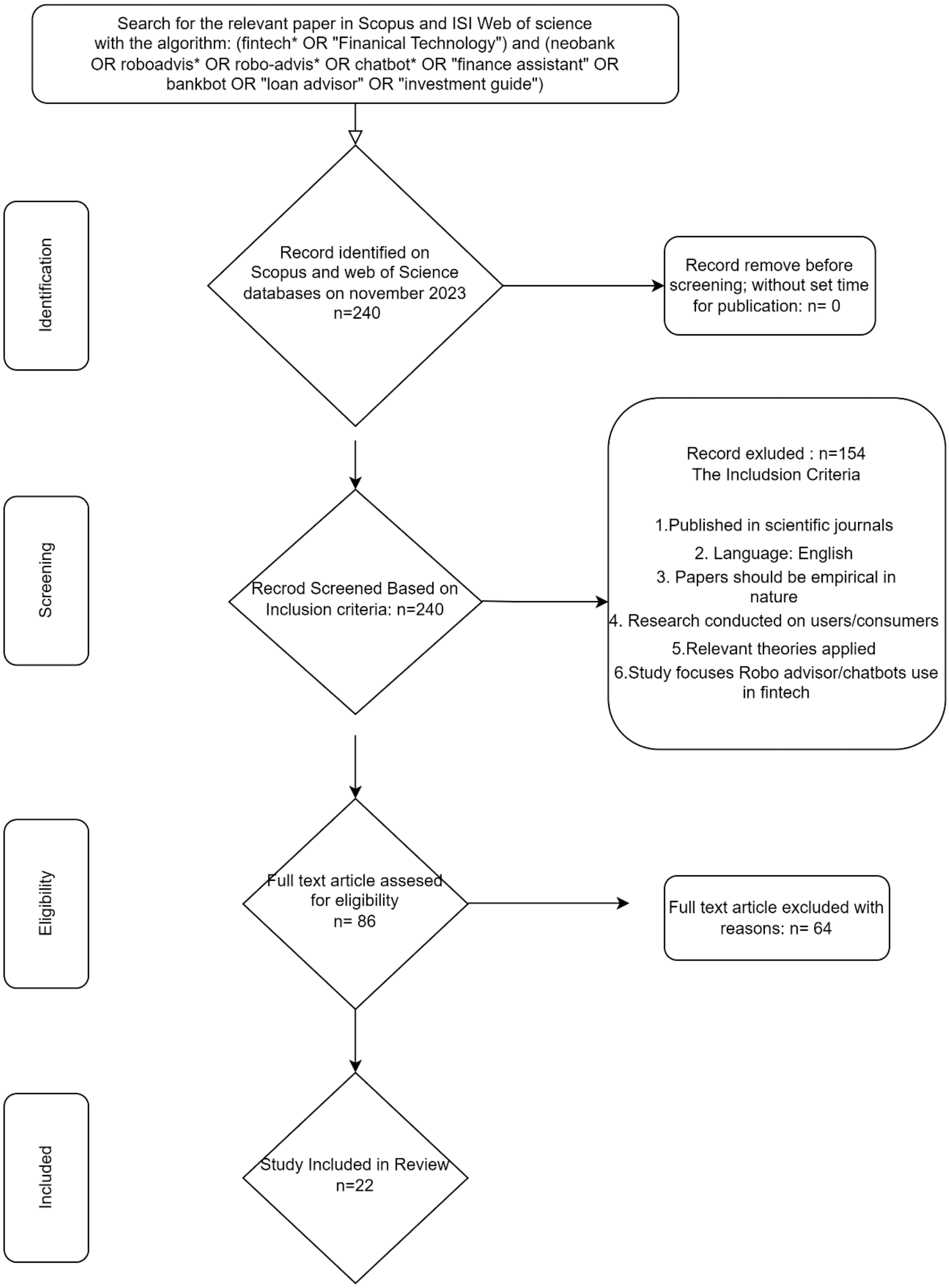

Figure 13 : Document Selection (Source: Author)

In order to clarify the procedure of literature selection for our research on the adoption of Robo-advisors in the field of financial technology, we utilized the PRISMA framework, as depicted in Figure 13. The researchers did an initial extensive search in the Scopus and Web of Science databases using a carefully constructed string of relevant keywords. The selected keywords encompassed concepts pertaining to Fintech and automated investment advisers, commonly referred to as Robo-advisors. These phrases include "Neobank," which denotes a digital bank that operates only online; "Robo-advisors," which are automated platforms that provide investment advice; "chatbot," which refers to an artificial intelligence program designed to engage in conversation; "finance assistant," which denotes a digital tool that aids in financial management, "bankbot," which refers to a chatbot specifically designed for banking services, "loan advisor," which denotes an automated system that offers guidance on lending options, and "investment guide," which refers to a digital resource that provides information and recommendations on investment strategies. A comprehensive examination of the data resulted in the identification of 240 individual entries.

In the screening phase, a total of 240 records were evaluated based on our predetermined inclusion criteria. These criteria stipulated that the studies should be published in scientific journals, written in English, possess an empirical nature, center around users/consumers, and incorporate applicable theories. There was no prior exclusion of data based on publication date prior to the screening process.

During the eligibility phase, a comprehensive evaluation of 86 publications was conducted to determine their pertinence to the research's primary objective, which is the examination of Robo-advisors in the field of financial technology (Fintech). The rationale for excluding certain studies at this juncture was based on their limited examination of the key determinants of customer adoption of Fintech. Some of these studies primarily focused on the adoption of Fintech solutions by banks, the influence of Fintech on customer retention, the adoption of artificial intelligence by Fintech and large corporations, or the effects of Fintech on financial inclusion in societies with varying income levels.

Following a meticulous and thorough screening procedure, a total of 22 studies were determined to be eligible and then incorporated into the final evaluation. These studies have explicitly examined the aspects that influence adopting and utilizing Robo-advisors or chatbots in the fintech business. They have contributed a concentrated body of literature that may be utilized to derive conclusions for our study aims.

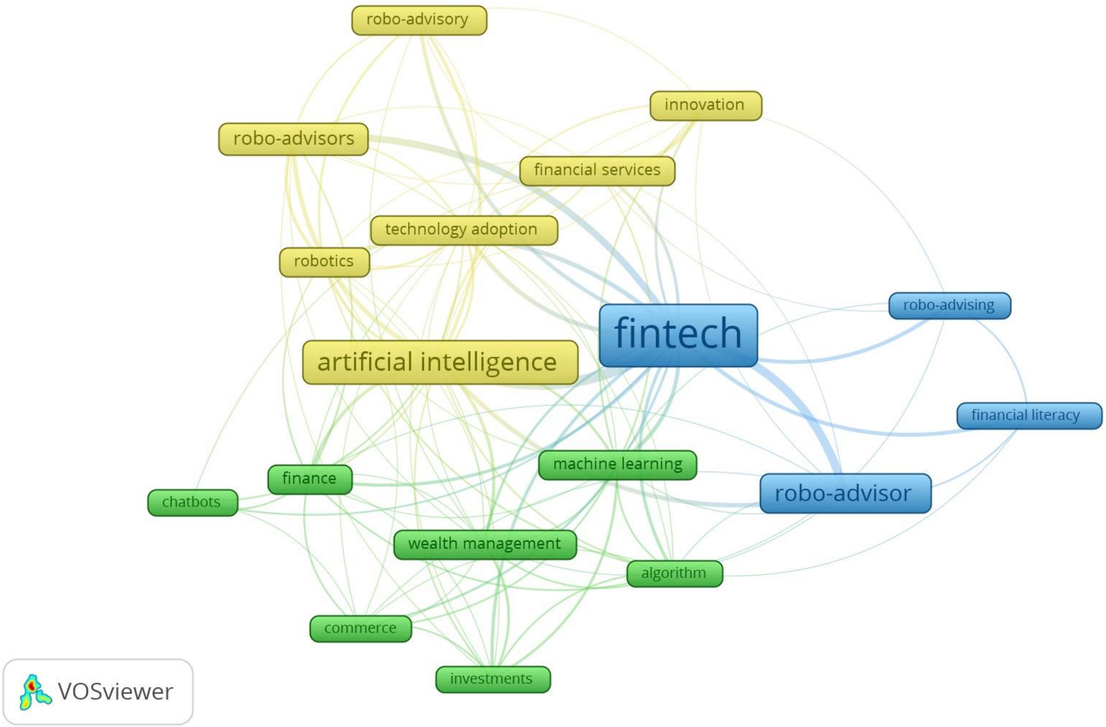

Figure 14 : Keyword analysis of 86 articles (source: Author)

The visualization in Figure 14 is a bibliometric network representation generated from the data retrieved from the first selection of 86 articles as part of the systematic literature review process. The network map, which is most likely produced using a program such as VOSviewer, visually represents the co-occurrence of terms in the dataset. This map effectively showcases the prominent and interrelated issues in the literature about Robo-advisors in the Fintech industry. This included the article before the eligibility part of the article selection.

6.2.3 Analyzing the Network Visualization

The central nodes are the key components or entities inside a network or system that are crucial to its overall structure and functioning. The image highlights the major role of 'Fintech' within the area, indicating its wide-ranging significance and prominence. The terms 'Robo-advisor' and 'artificial intelligence' are extensively incorporated in the surrounding context, highlighting their notable presence and importance in the ongoing Fintech conversation.

Interrelated Themes: Multiple clusters of interrelated topics can be identified. For example, a tight correlation exists between the term 'Robo-advisors' and the domains of 'wealth management' and 'investments,' implying a robust connection between the utilization of automated advising services and these specific realms within the field of finance.

The clusters depicted in different colors serve as visual representations of interconnected thoughts or topics. Keywords within the same cluster exhibit a higher degree of interconnectedness compared to keywords located in separate clusters. An illustration of this may be seen in the grouping of terminology such as 'machine learning,' 'algorithm,' and 'artificial intelligence,' which together pertain to the technological foundations of Robo-advisors.

The dimensions of the nodes in the visual representation correspond to the frequency of occurrence of the keyword throughout the body of literature. Nodes that are greater in size reflect phrases that are referenced more frequently. The lines, also known as edges, connecting nodes in the network diagram indicate the degree of correlation between phrases, with thicker lines indicating a higher frequency of co-occurrence.

The inclusion of terms such as 'chatbots,' 'robotics,' and 'technology adoption' in conjunction with 'Fintech' and 'Robo-advisors' suggests that scholarly literature on this subject matter not only focuses on the technical aspects of these technologies but also explores the process of their adoption and integration within the wider financial services ecosystem.

The intersection between innovation and services. Including the term 'innovation' in conjunction with 'financial services' and 'Fintech' suggests that scholarly literature acknowledges the disruptive nature of Fintech, particularly Robo-advisors, as innovative agents that challenge established norms in traditional financial services.

The presented visualization functions as a strategic instrument for discerning the fundamental research domains and the most prominent subjects within the realm of Robo-advisors in financial technology. This compilation offers a comprehensive overview of the scholarly terrain, showcasing the extensive scope and range of investigations undertaken in relation to these subjects. A map of this nature may provide valuable assistance to academics and practitioners in comprehending the primary areas of attention, recognizing deficiencies in the existing body of literature, and making projections regarding the trajectory of the subject. This, in turn, can serve as a guiding framework for future research endeavors and practical applications.

6.3 Results and Discussion

6.3.1 Publication Year

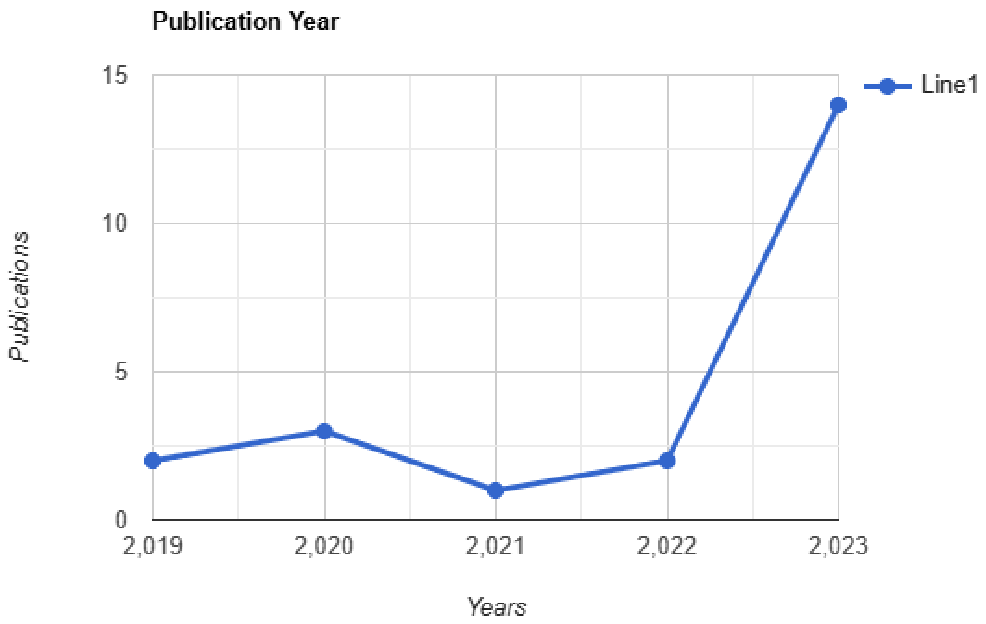

Figure 15: Publication Year (source: Author)

The graphical representation in Figure 15, entitled "Publication Year," illustrates the distribution of scholarly articles on adopting Fintech throughout different years. It effectively showcases an increasing tendency in the quantity of research papers produced in this particular domain. The visual representation consists of a bar graph and a line graph, illustrating the annual count of publications, which has an evident upward trend in recent years.

The x-axis denotes the temporal dimension from 2017 to 2023, while the y-axis quantifies the volume of articles. The vertical bars represent the number of research publications that have been published annually, while the line graph depicts the general pattern seen throughout the years.

The graph clearly illustrates that there was just one publication in the year 2017, indicating the first phase of research on Fintech uptake. Over the course of time, a variable but predominantly increasing trend has existed in the quantity of published works.

Based on the data obtained for the year 2023, which comprises a total of 14 articles, it can be inferred that there is a sustained and strong inclination for Fintech research in the context, thus reflecting a persistent increasing trend. Given that the data collection for this project was terminated in November 2023, the count for the current year encompasses research interest up until that specific interval.

Table 11 Journals of Documents and Publishers

Journals of Documents, Quratiles, Pubslihers, SJRs

BEST SCOP..	Journal	Publisher_Category	SJR
Q1	Asia Pacific Journal of Marketing and Logistics	Emerald	0.770
	Computers in Human Behavior	Elsevier	2.460
	Industrial Management and Data Systems	Emerald	0.660
	Journal of Behavioral and Experimental Finance	Elsevier	1.240
	Journal of Electronic Commerce Research	California State University Press	0.800
	Journal of Service Management	Emerald	2.880
	Journal of Theoretical and Applied Electronic Commerce Research	MDPI	0.450
	Sensors	MDPI	0.360
	Service Industries Journal	Taylor and Francis	0.460
	Sustainability (Switzerland)	MDPI	2.000
Q2	Data and Information Management	Elsevier	0.760
	Frontiers in Artificial Intelligence	Frontiers	0.740
	International Journal of Bank Marketing	Emerald	0.460
	Journal of Financial Counseling and Planning	Springer	2.640
	Journal of Financial Services Marketing	Palgrave Macmillan	1.220
	Mathematics	MDPI	0.140
Q3	Business Perspectives and Research	SAGE	1.880
	Journal of Indonesian Economy and Business	Gadjah Mada University	0.180
Q4	Journal of Global Business and Technology	Global Business and Technology Associ..	1.090

Sum of SJR for each Publisher_Category broken down by BEST SCOPUS QUARTILE and Journal. The marks are labeled by sum of SJR. The view is filtered on Journal, which excludes Telematics and Informatics.

Table 10 represents a comprehensive overview of the academic journals that have published research on the adoption of financial technology (Fintech). The journals are categorized based on their Scopus quartile rating and their corresponding SCImago Journal Rank (SJR). The data presented in the table demonstrates that research papers in the field of Fintech are dispersed throughout journals of different rankings. Notably, a considerable representation in Q1 journals suggests that a substantial proportion of Fintech research is published in esteemed academic publications. For example, the journals 'Computers in Human Behavior' and 'Journal of Service Management,' which are both classified as Q1 journals, exhibit notable SJR scores of 2.46 and 2.88, respectively. These scores serve as indicators of the significant effect these journals have in the dissemination of research with substantial significance. The 'Asia Pacific Journal of Marketing and Logistics' and 'Telematics and Informatics' are both considered Q1 journals, indicating that they are among the highest-ranked journals in their field. This suggests that top-tier journals are a key outlet for accessing the most advanced research on this topic.

The presence of a wide range of publishers, such as Emerald, Elsevier, SAGE, and Taylor & Francis, is indicative of the multidisciplinary character of Fintech research. This is evident via the diverse contributions that encompass several subjects and viewpoints. The variation in SJR ratings, ranging from 0.14 in the field of Mathematics to 2.64 in the Journal of Financial Counseling and Planning, indicates the diverse range of journals covering Fintech adoption. This suggests that the research of Fintech adoption is approached from several perspectives, encompassing both specialist and general publications. The incorporation of journals such as 'Sustainability (Switzerland)' with a Scimago Journal Rank (SJR) of 2 and 'Business Perspectives and Research' with an SJR of 1.88, even within the third quartile (Q3), indicates that the study of Fintech adoption is increasingly attracting attention from various academic fields, extending beyond prestigious publications.

6.3.2 Determinants of Robo-Advisor Adoption Fintech

Considering the SLR technique employed in the study, self-constructed and theoretical frameworks are seen as significant while developing the Robo-advisor base. The following table will help to illustrate the Robo-advisors' determinants, including Significant IVs (Independent Variables) and DV (Dependent Variables)

Table 12 Significant IVs, Theories, and DV's

Significant IV's, Theory, DV's

			DV		
Significant Independent Behavior	Paper ID	Theory	BEHAVI..	INTENTI..	TRUST
ANTH (+), SE (+),CAICE (+),	36	SOR		■	
EE (+), SI (+), TRU (+),	59	UTAUT		■	
EE(+), PI(+), ATI (+)	30	UTAUT, SCT, HET		■	
EOU (+), USEF(+), PLEA(+), AROU(+),	72	TAM		■	
EPS(+), RAS(+), FS(+),CT(+)	69	TAM			■
FK (+), AIK (+), IRT (+), CCC (+), BFK (-), BAIK (-), IC&O (+), UTPS (+), UOM (+), NTFT (+)	27	DOI		■	
FK (+), PU (+), PT (+)	58	N/A		■	
Investor's Risk Profile(+), location US (+) GER (-)	3	N/A	■		
Optimism(+), Insecurity(-), Awareness (+)	11	TRI		■	
PANI(+), PANTH (+), PINT (+), SP(+), TSE (+), HA (+),UA (+)	41	TRA, TAM, SOR	■		
PE (+), EE (+), SI (+), FC (+)	60	UTAUT		■	
PE (+),EE(+), SI(+), FC(+), PP(+), T(+)	17	UTAUT	■		
PENJOY (+), ANTHRO (+), PERPRO (+), COMP (-), TRU (-), PERSEC (-), PERRISK(-)	51	DFM		■	
PEOU (+), PU (+),AT (+), SN (+)	32	TAM		■	
PEUSE (+), PECON (+), PUSEF (+), ATT (+)	57	TRI		■	
PJU (-), PCON (+), PINT (+)	49	SOR	■		
PRAC(+), ENJOY (+), PERSON(+), PRIV CONCERN(-), CREEP(-),	67	TAM		■	
PUSE (+), PERPRIV (+),	76	TAM		■	
RA (+), COM (-), HM (+), PI (+), AT (-), PR (-)	22	UTAUT2		■	
RE (+), IQ(+), SQ(+), AA (+), SC (+), GR (+) , TV (+), TT (+),SC (+)	31	TTT			■
ROBO-USER (-), Trust(-), Gender(female) (+),	1	N/A	■		
SIC (+), SCC (+), SLC (+), EA (+)	8	SRT		■	

DV
BEHAVIOR
INTENTION
TRUST

DV (color) broken down by DV vs. Significant Independent Behavior, Paper ID and Theory.

The table illustrates the relationship between independent and dependent variables as seen in 22 carefully chosen research.   These investigations primarily focused on three dependent variables: behavior, intention, and trust.   Trust was examined as a dependent variable in just two articles, while behavior and intention were investigated as dependent factors in 5 and 15 papers, respectively. The Technology Acceptance Model (TAM) served as the theoretical foundation in six publications, whilst the Unified Theory of Acceptance and Use of Technology (UTAUT) provided the framework for four investigations. Two publications were supported by the Stimulus-Organism-Response (SOR) model and the Theory of Reasoned Action (TRA), respectively. Furthermore, the remaining publications utilized several theoretical frameworks, such as Social Cognitive Theory (SCT) and Diffusion of Innovations (DOI). Significantly, three publications did not conform to any particular theoretical framework.

Regarding the impact of important independent variables, it was discovered that Perceived Usefulness and Perceived Ease of Use had a favorable influence on user behavior and intentions, as demonstrated in four publications. Three studies showed a positive correlation between Performance Expectancy (PE) and user intention and behavior. Similarly, Effort Expectancy (EE) was associated with user intention and behavior in four articles. Three studies conducted in China, Taiwan, and Spain found a favorable correlation between Social Influence (SI) and user behavior and intention. Facilitating Conditions exhibited a favorable correlation in just two research conducted in China and Taiwan. This synthesis highlights the complex connections between user perceptions and the theoretical frameworks that influence Fintech user behavior and intents. The following 3D graph will help illustrate the dependent variables and theoretical framework used.

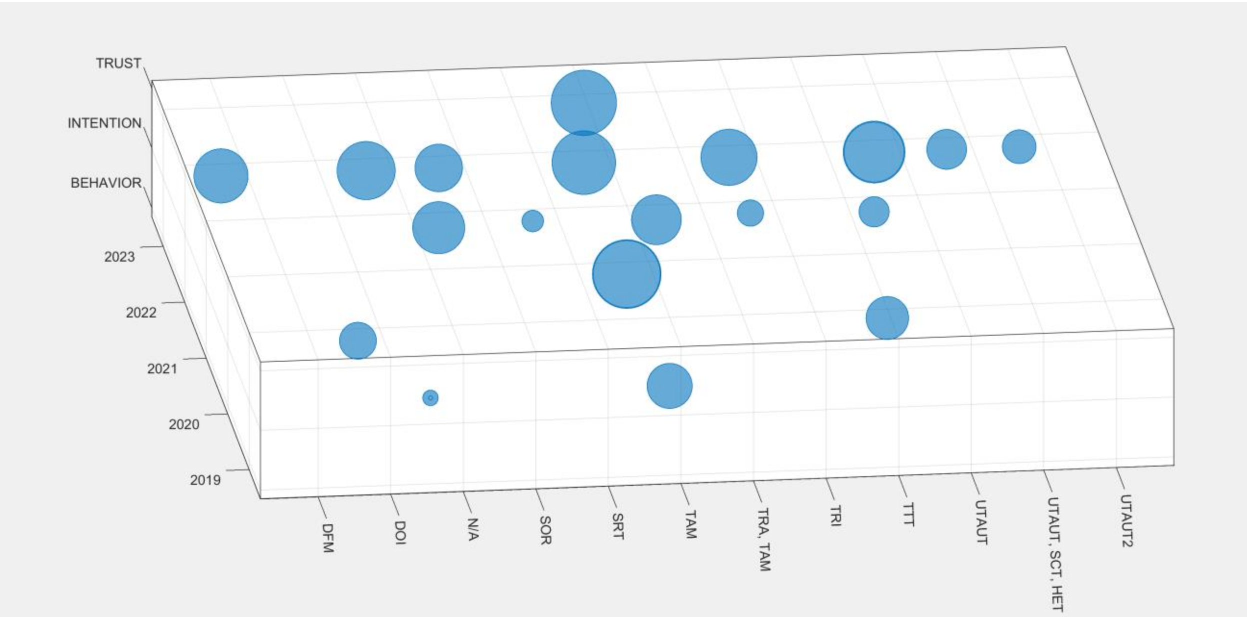

Figure 16 : 3D Graph on Theories, Years, and DV's

The 3D graph provides a thorough representation of the Fintech research landscape, highlighting the prominent influence of the Technology Acceptance Model (TAM) and the

Unified Theory of Acceptance and Use of Technology (UTAUT) as theoretical frameworks. These models are commonly used to analyze financial phenomena, with a strong emphasis on 'intention' as a dependent variable. This indicates an academic focus on the issues that impact users' willingness to embrace Fintech services.

In addition, the portrayal emphasizes that 'intention' is the outcome that has been studied most frequently, surpassing 'trust' and 'behavior' in terms of the number of research papers conducted. This highlights a pattern in Fintech research that focuses on comprehending the factors that influence users' intentions to adopt.

An examination of the data points indicates a clustering of studies in the year 2023, signifying it as a year of notable research activity in the field. This may suggest a recent rise in interest or even a gathering of data as study endeavors escalate. The graph clearly illustrates this pattern, showing a significant proportion of studies conducted in 2023 that focus on Fintech research. Specifically, these studies examine user intention as the primary variable of interest, indicating a continued and strong involvement in this area. Visual analytics in the Fintech sector helps to both identify the current study emphasis and provide insights for future scholarly efforts.

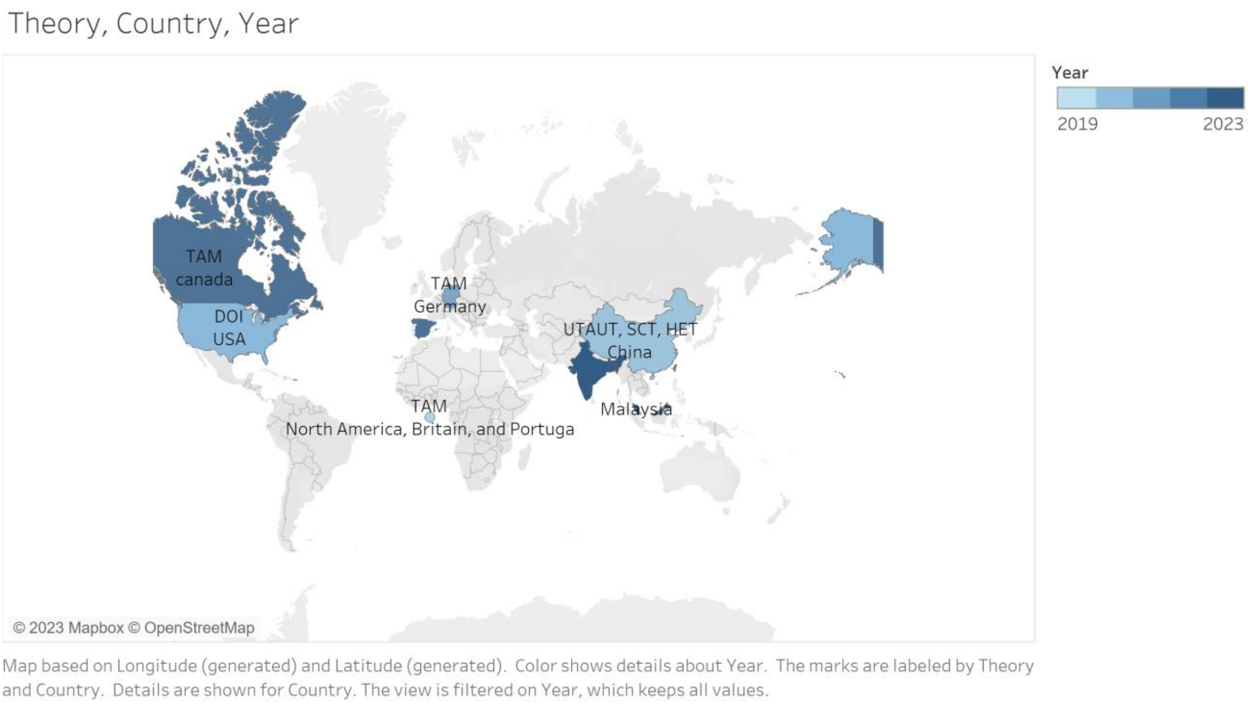

Figure 17 : Countries, Theories, Years

A systematic literature assessment of Robo-advisors in the Fintech sector is represented geographically by the above image. It describes how academic articles are distributed throughout different nations and covers the years 2019–2023.

6.4 Concepts and Frameworks

Abbreviations for theories and models that have probably been used in research conducted in several nations are marked on the map. These acronyms introduce a variety of theoretical frameworks that are frequently employed in the study of technology adoption and integration in industries such as Fintech:

The technology acceptance model, or TAM (Davis, 1987), is crucial for understanding how users will embrace new technologies. It is intended to forecast and clarify user acceptance of Robo-advisors. The fact that it shows up in multiple nations on the map suggests that Fintech research is using it widely throughout the world.

The Diffusion of Innovations (DOI)(Rogers et al., 2014) hypothesis aims to explain the how, why, and the rate at which novel concepts and innovations proliferate. The fact that DOI is present in the USA indicates that research has been conducted there on the market's Robo-advisor growth.

An expansion of TAM (Davis, 1987), UTAUT (V. Venkatesh et al., 2003) (Unified Theory of Acceptance and Use of Technology) takes into account extra elements like social influence and enabling circumstances. Its mention in China might be a result of research looking at all the variables impacting Robo-advisor acceptance.

Though they are not as well-known as TAM (Davis, 1987)or UTAUT (V. Venkatesh et al., 2003), SCT (Social Cognitive Theory) (Bandura, 1969), and HET (Hedonic Motivation System Adoption Model) (Lowry et al., 2012) can be utilized in Fintech research to look at the psychological and social aspects that affect Robo-advisor adoption.

Geographical Insights: The countries marked on the map—the United States, Canada, Germany, China, and Malaysia—indicate a geographical distribution throughout Europe, Asia, and North America. This indicates that Robo-advisor implementation is of worldwide interest, as evidenced by studies coming from both developed and emerging economies.

Temporal Elements:

The data is given a time dimension by the color coding, whereby varying hues of blue signify the study years ranging from 2019 to 2023. A deeper tint might indicate more recent or extensive research. The progression of Robo-advisor technology and its incorporation into financial services could be monitored over time with the help of this temporal data.

The study grouped the determinants into six clusters to explain the effect.

6.4.1 TAM-Related Determinants

In order to clarify the elements that affect the adoption of Fintech, our collection of academic literature mostly uses the Technology Acceptance Model (TAM), which is derived from the Theory of Reasoned Action (TRA). TAM, founded by Davis in 1989 (F. D. Davis, 1989), offers a conceptual framework for understanding how individuals embrace and utilize new technology. Belanche et al. (2019b) examined their dataset's North American, British, and Portuguese markets. They identified that Perceived Ease of Use and Perceived Usefulness are important factors that influence the intention to use financial Robo-advisors. Other research results, including those conducted in India, support the same conclusions. Upadhyay and Kamble (2023a) utilize the Stimulus-Organism-Response (SOR) model to explain the appeal of mobile banking Robo-advisors in the Indian context. They identify anthropomorphism and smart experience as significant variables that contribute to this appeal.

Priya and Sharma (2023) extend the TAM framework by examining the adoption intentions of intelligent virtual assistants in the financial services sector in India. They emphasize various anthropomorphic and socio-psychological aspects, such as Perceived Animacy and Technological Self-Efficacy, which influence user behavior towards these technologies. In a study conducted by Aw, Leong, et al. (2023), the researchers used the S-O-R framework to analyze the resistance towards Robo-advisors. The findings showed that perceived Justice and Privacy Concerns can occasionally hinder the acceptance of Fintech.

The dataset incorporates the study of Ashrafi and Kabir (2023), which utilizes the dual-factor model to evaluate the primary factors influencing customers' adoption of financial Robo-advisory services. The study highlights the positive impact of Perceived Enjoyment and Anthropomorphism while also identifying Perceived Risk as a discouraging factor. Sabir et al. (2023) confirm the importance of Perceived Ease of Use and Perceived Usefulness, as described in the Technology Readiness Index (TRI), in influencing the desire to adopt AI Robo-advisors in the Chinese market.

In their study, Yi et al. (2023) specifically investigate millennials' usage of Robo-advisory services in Malaysia. They identify Financial Knowledge, Perceived Usability, and Perceived Trust as crucial factors that drive their inclination to accept these services. These findings are supported by research conducted by de Andrés-Sánchez and Gené-Albesa (2023b) in Spain and Yeh et al. (2023) in Taiwan. These studies utilize the UTAUT framework to confirm that effort expectancy, social influence, and facilitating conditions have a significant influence on promoting the intention to use such technologies.

Overall, TAM and related theories form the basis for most studies in our dataset. However, including different geographical contexts and integrating other theoretical perspectives like SOR and TRI provide a comprehensive and multifaceted understanding of the factors that influence the acceptance and adoption of Robo-advisors in the Fintech industry.

6.4.2 UTAUT and UTAUT 2 related determinants

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a fundamental theoretical concept in the field of Fintech, namely in the implementation of Robo-advisors. A group of researchers in our dataset utilize UTAUT and its sequel, UTAUT2, to analyze the complex network of factors influencing the adoption of these automated financial services. These studies cover different geographical areas and emphasize UTAUT's concepts' universal nature.

In the case of Spain, de Andrés-Sánchez and Gené-Albesa (2023b) utilize the UTAUT framework to clarify policyholders' acceptance of Robo-advisors. They emphasize that Effort Expectancy (EE) and Social Influence (SI) are factors that positively influence acceptance, while Trust plays a crucial role in creating Behavioral Intention. In a similar manner, Yeh et al. (2023) utilize the UTAUT to examine the adoption of Robo-advisors in Taiwan. Their findings confirm that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) have a favorable impact on Behavioral Intention.

By comparing these findings with the study conducted by Roh et al. (2023) that used both the UTAUT and the Theory of Reasoned Action (TRA) in China, a clear and consistent trend can be observed: the factors of Perceived Enjoyment (PE), Perceived Ease of Use (EE), Social Influence (SI), and Facilitating Conditions (FC) are all positively linked to the acceptance and use of AI-enabled Robo-advisors. Additionally, the factors of privacy and trust also contribute to the overall effectiveness of the model. Ashrafi (2023) expands upon the UTAUT framework by introducing UTAUT2 to better understand the complexities in Bangladesh. This study identifies Relative Advantage, Hedonic Motivation, and Perceived Innovativeness as factors that enhance Perceived Value and Behavioral Intention. Additionally, it finds that Attitude toward AI and Perceived Risk has a negative relationship with Adoption Intention.

The application of UTAUT extends beyond these regions exclusively. Fan and Swarn (2020) offer a viewpoint different from that of the United States by combining the diffusion of innovation theory with information search frameworks to examine how individual investors use robo-advisors. They identify various knowledge-related and behavioral factors that influence the likelihood of adopting these services. Furthermore, Aw, Zha, et al. (2023) combine UTAUT with Social Contract Theory (SCT) and Humanizing Experience Theory (HET) to analyze the adoption of Robo-advisory services in China. They suggest that factors such as emotional experience (EE), perceived intellect, and affinity for technological interaction have a significant impact.

These various studies, based on the UTAUT and UTAUT2 models, show that the factors influencing the acceptance of Robo-advisors are complex and go beyond traditional concepts. They include factors such as knowledge, personal attitudes, and the intricate relationship between technology and human experience.

6.4.3 SOR-related Determinants

Two prominent research within the 22 publications on Fintech adoption highlight the relevance of the Stimulus-Organism-Response (SOR) framework. This framework posits that certain stimuli (S) exert an influence on the internal state of the organism (O), subsequently resulting in a reaction (R).

Upadhyay and Kamble (2023b) utilize the SOR model to analyze the attractiveness of mobile banking Robo-advisors in India. Their research suggests that the human-like characteristics of Robo-advisors, the intelligent experience they offer, and the amount of interaction they promote serve as triggers that have a beneficial impact on customers' mental states, ultimately leading to a desire to embrace these Robo-advisors as a beloved brand.

Priya and Sharma (2023) concurrently utilize the SOR framework in conjunction with TRA and TAM to examine the inclination to embrace intelligent virtual assistants in the financial services sector. The authors cite perceived animacy and anthropomorphism, which are markers of the social presence of AI and technological self-efficacy, as important triggers. These aspects impact the user's mental state, impacting both their pleasure-seeking and practical attitudes, subsequently determining their behavioral reaction to such services.

In addition, Aw, Zha, et al. (2023) examine the negative aspects of Robo-advisors by utilizing the SOR framework to comprehend how customers' perceptions of justice and intrusiveness impact their internal states related to privacy concerns. This, in turn, may result in a behavioral response characterized by resistance to adopting Robo-advisors.

Utilizing the SOR model, these two studies offer a valuable understanding of the psychological and emotional processes that motivate user engagement and adoption of Fintech applications. They indicate that user responses are influenced by functionality and usability as well as experiential and affective engagements with the technology. These interactions play a crucial role in molding the whole user adoption process in the field of Fintech.

6.4.4 TRI-related Determinants

The Technology Readiness Index (TRI) has played a crucial role in analyzing the factors that influence the acceptance and implementation of Robo-advisors in the Fintech industry. The study conducted by Flavián et al. (2022) utilizes the Technology Readiness Index (TRI) to assess the inclination to utilize analytical artificial intelligence (AI) systems, such as Robo-advisors, within the United States setting. The study reveals that the level of 'Optimism' towards technology, which is a fundamental aspect of TRI, has a beneficial impact on user intention. Conversely, 'Insecurity' has a detrimental effect. Moreover, clearly understanding the technology's potential enhances the willingness to embrace these AI services.

This is consistent with the results of (Sabir et al., 2023) study conducted in China, where the Technology Readiness Index (TRI) was used to assess customer adoption of AI Robo-advisors directly. Their research emphasizes that characteristics such as 'Perceived Ease of Use' and 'Perceived Usefulness,' which are conceptually akin to 'Optimism' in TRI, vigorously promote the desire to adopt Fintech innovations. Furthermore, a positive inclination towards technology, indicating a willingness to interact with AI applications, is also a good factor.

These studies emphasize the importance of the TRI framework in analyzing user attitudes toward emerging technologies in the financial sector. The aspects of 'Optimism' and 'Insecurity' in the TRI are used to predict user intention. They show that individuals' technological viewpoints and comfort levels are important factors in shaping the adoption of Robo-advisors.

6.4.5 Other Theories Related Determinants

Various theoretical frameworks have been used to examine user behavior and intention in order to understand the factors that influence the adoption of Robo-advisors in the Fintech industry.

These ideas provide a comprehensive perspective on the various elements that impact the acceptance of AI-powered financial consulting services.

Huang and Lee (2022b) examine the social dynamics of user engagement with financial Robo-advisors by employing the Social Response Theory (SRT). The study reveals that factors such as Social Interactivity and Social Credence, along with the emotional arousal triggered by these interactions, have a beneficial impact on the desire to continue using these services in Taiwan.

Fan and Swarn (2020) employ Diffusion of Innovation Theory and Information Search Models to investigate the adoption of Robo-advisors by individual investors in the United States. Subjective financial knowledge and investment risk tolerance increase the probability of adoption, while objective knowledge may not have a similar impact.

Aw, Zha, et al. (2023) combined UTAUT, Social Contract Theory (SCT), and Humanizing Experience Theory (HET) to analyze the adoption of robo-advisory services in China. Their findings indicate that user acceptance is highly influenced by factors such as effort expectancy and Perceived Information Quality.

In their study, they Utilized Trust Transfer Theory (TTT) to investigate the trust mechanism in robo-advisor services in China (Shoukat et al., 2025). They identify reputation, information quality, and service quality as the primary elements that contribute to the establishment of trust.

This research suggests that adopting Robo-advisors depends on psychological and functional factors. The importance of social elements, trust, perceived usefulness, and personal attitudes towards technology is repeatedly emphasized in many cultural and geographical settings, emphasizing the worldwide relevance of these variables in the Fintech industry.

6.4.6 Self-Developed Constructs

Some studies in the Fintech sector have developed original models to understand the factors that influence Robo-advisors' acceptability. However, these studies have not based their findings on recognized theoretical frameworks.

The study conducted by Brenner and Meyll (2020) in the United States adopts an empirical and quantitative methodology to examine the characteristics of 'ROBO-USER' and establishes a negative association with the utilization of Robo-advisers. Trust exhibits a negative correlation; however, gender demonstrates a fascinating positive correlation, indicating that women are more inclined to utilize Robo-advisers.

The study conducted by Boreiko and Massarotti (2020) explores the relationship between investors' risk profiles and the use of Robo-advised portfolios in both the USA and Germany. In the US, investors with a positive risk profile tend to allocate a greater proportion of their investments to Robo-advised portfolios. Conversely, in Germany, a negative relationship exists between risk profile and investment in Robo-advised portfolios. This suggests that geographical considerations may influence the adoption of Robo-advisory services.

In this study, Yi et al. (2023) examine the utilization of Robo-advisory services by Malaysian millennials, a population recognized for early technology acceptance. Their research emphasizes that financial knowledge (FK), perceived usability (PU), and perceived trust (PT) have a strong beneficial impact on the readiness to accept Robo-advisors. Millennials' proficiency with technology, ease of utilizing it, and degree of confidence in the systems play a crucial role in incorporating Robo-advisory services into their financial endeavors.

These studies collectively indicate several individual and contextual elements influencing behavioral intentions toward Robo-advisors. The lack of a cohesive theoretical framework in these studies suggests that the field is still in the process of investigating and determining the most relevant factors. This implies that future research could be enhanced by creating a more customized theoretical model that encompasses the distinct characteristics that influence the adoption of Robo-advisors.

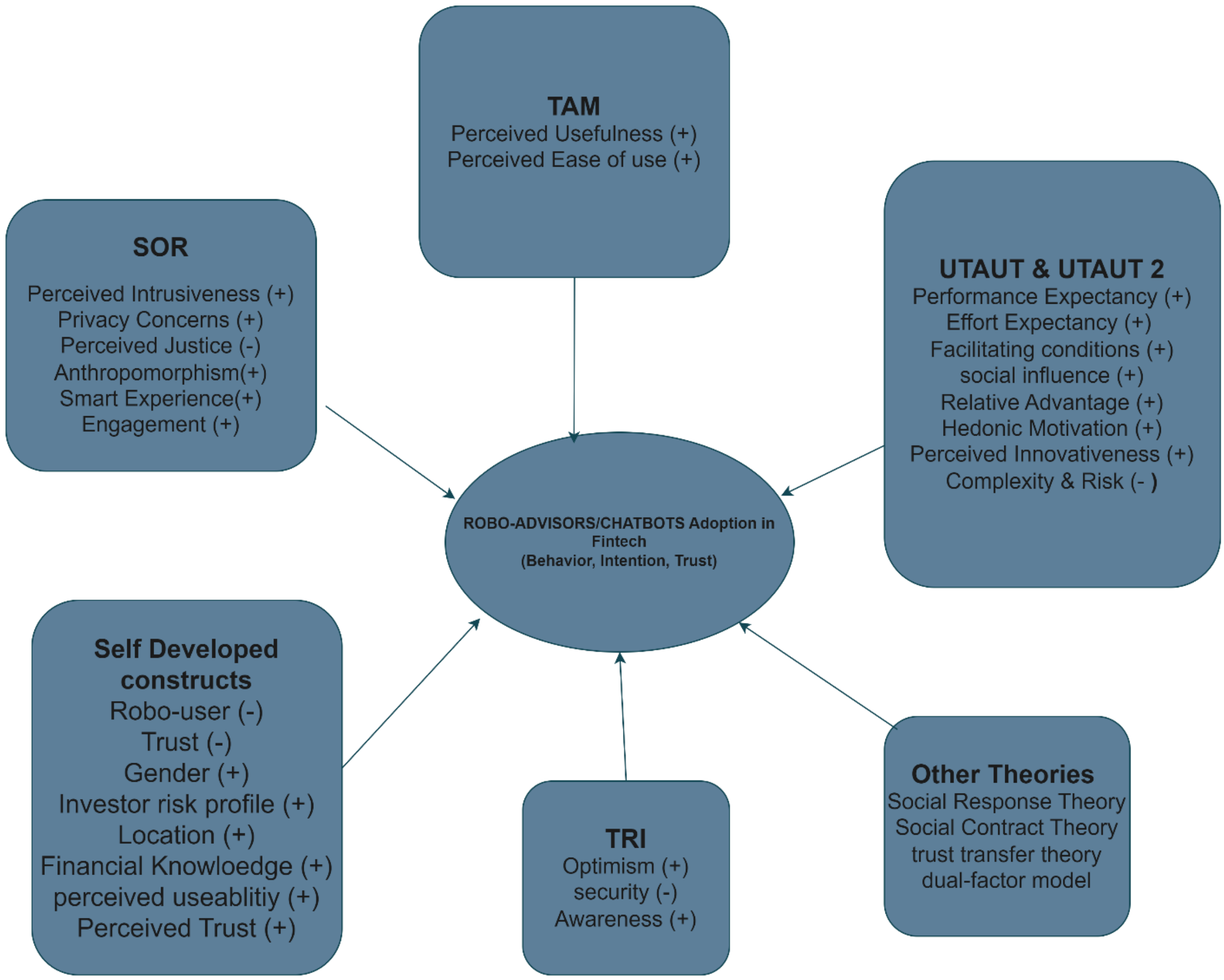

Figure 18 : The proposed framework of Robo-advisor adoption in Fintech determinants in literature

6.5 Conclusions

This study has identified key factors that influence the acceptance and implementation of Robo-advisors and chatbots in the Fintech industry through a comprehensive analysis of scholarly literature. A rigorous evaluation approach using the Scopus and Web of Science databases enabled the selection of crucial documents, which were then examined to uncover fundamental theoretical concepts that influence the adoption of Fintech.

Studies lacking certain theoretical frameworks have uncovered distinct, internally created structures that substantially impact consumer behavior and the inclination to utilize Robo-advisors. Brenner and Meyll (2020) found that negative sentiments towards Robo-advisors, lack of trust, and unexpectedly, a positive association with being female influence the utilization of Robo-advisory services in the United States. Similarly, Boreiko and Massarotti

(2020) discovered that an investor's risk tolerance and geographical location (with US investors being more favorably disposed than their German counterparts) influence their level of involvement with Robo-advised portfolios.

A comprehensive examination that integrates various theoretical frameworks, including Social Response Theory, the Technology Readiness Index, and the Unified Theory of Acceptance and Use of Technology, uncovers an intricate interaction of components such as social cues, emotional arousal, optimism, and perceived ease of use. The research encompasses several nations, including Taiwan, the USA, and Germany, suggesting that both social and individual psychological aspects play a crucial role in influencing the intention to continue using and the overall acceptance of Fintech solutions.

To summarize, this study emphasizes the various theoretical foundations, such as TAM and UTAUT, that explain the mechanics of Fintech acceptance and recognize the significance of self-created concepts. The virtual nature of client interactions with Fintech platforms necessitates strong levels of trust in order to maintain durable customer relationships. Trust is particularly important in this context.

This contribution is noteworthy as it presents a thorough framework of factors that determine the adoption of Fintech, providing a nuanced comprehension for both academic and practical purposes. It motivates future scholars to investigate both well-established theories and experiment with novel constructions. These insights are extremely significant for Fintech organizations as they help to cultivate customer loyalty and adjust to the ever-changing nature of consumer preferences.

The study's shortcomings, such as merging actual usage and behavioral intention and relying solely on Scopus and Web of Science as data sources, create opportunities for future research to enhance and fine-tune this analysis. Future research should explore the inclusion of supplementary databases to encompass a broader range of data, thereby enhancing the comprehension of factors influencing the adoption of Fintech, specifically in relation to Robo-advisors and chatbots.

7. Robo-Advisors Acceptance

The advent of Robo-advisors, which are sophisticated algorithms capable of emulating human speech, has brought about a transformative change in the manner in which individuals interact with computer systems. Initially introduced in 2016 (Brandtzaeg & Følstad, 2017), Robo-advisors have rapidly become an essential component of immediate customer support, providing instantaneous responses to inquiries on products and services. Their 24/7 connectivity, cost-effectiveness, versatility, and user-friendly interface make them attractive to both end-users and corporations (Gundu et al., 2022). Given these characteristics, it is not surprising that 80% of organizations are now using or expressing a desire to use Robo-advisors (Skrebeca et al., 2021). This is especially accurate in domains where they have substantial influence, such as marketing and customer assistance. Robo-advisors have enhanced their intelligence through the integration of cognitive technologies, enabling them to closely replicate human cognitive abilities. Robo-advisors utilize machine learning, cognitive computing, and natural language processing technology to effectively address complex problems and interact with individuals. Cognitive computing truly excels in cases with intricate issue areas or several potential solutions. Cognitive Robo-advisors are revolutionizing several sectors, such as banking, by creating new business opportunities and transforming markets. They are actively fostering innovation and generating substantial value. Machine learning methods utilize large amounts of data to enhance financial decision-making and marketing tactics, creating a focal point for collaborative discussions on the intersection of cognitive technology and Fintech.

The academic study on customizing Robo-advisors and providing context-aware customer assistance has been insufficient despite the extensive utilization of Robo-advisors across several businesses. The D&M approach and the Technology Acceptance approach (TAM) are limited to account for the numerous intricacies involved in chatbot-assisted customer support. Trust and satisfaction in online interactions are extremely significant, especially when personalized service is expected to significantly influence purchase decisions. Additional research is necessary to explore personalization in financial services due to the scarcity of scholarly literature on this subject. This research aims to impartially evaluate the efficacy of intelligent Robo-advisors in delivering sophisticated, contextually sensitive customer support, transcending exaggerated claims, and focusing on real-life financial user interactions. This is because research on the adoption of Robo-advisors technology is still in its nascent phase.

Humans are engaged in communication activities with today's software system, which also communicates in human languages such as English and is called "*chatbots*" (Shawar & Atwell, 2007). Robo-advisors have become the face of significant technological innovation since 2016 (Johannsen et al., 2021). It's very easy to get real-time information about services or products using Robo-advisors (Cordero et al., 2022). End-users and businesses consider the convenience of using Robo-advisors due to their low cost, versatility, and simplicity (Kaushal & Yadav, 2023). 24/7 connectivity and available solutions with Robo-advisors have become the reason around 80 percent of businesses are using or expected to implement Robo-advisors (Melián-González et al., 2021). Areas such as marketing, support, and sales intensively experience Robo-advisors' services 24/7 (Ashfaq et al., 2020). Marketing (55%) and Customer service (95%) have widely been implemented by Robo-advisors (Behera et al., 2021).

Robo-advisors exhibit cognitive abilities and behaviors that are similar to those of humans. Various cognitive technologies enable the Robo-advisors' capabilities, including machine learning, cognitive computing, artificial intelligence, natural language processing, deep learning, and other related technologies. These technologies enhance the cognitive system of the Robo-advisors, enabling them to effectively engage with their environment and other individuals and find innovative and creative solutions to problems. Cognitive technologies include Natural Language Processing, Cognitive Computing (CC), Natural Language Understanding, and Machine Intelligence (ML) (de Arriba-Pérez et al., 2023). When a single query yields several viable hypotheses or when the problem area is exceedingly complicated, CC systems are frequently employed to tackle the issue (Hurwitz et al., 2015). Numerous businesses and academic institutions presently employ machine learning (Ferrettini, 2021). Cognitive chatbots (CC) no longer require access to a restricted set of preprogrammed responses or a small quantity of data. The cognitive capabilities of Robo-advisors allow them to use the benefits of personalization and context.

The research of CC has highlighted the importance of cognitive technologies in business-to-business interactions, which has led to the development of new marketing strategies and the incorporation of the Internet into decision-making processes and a vast array of corporate operations (Rajagopal et al., 2022). The influence of CC technology, particularly innovation and value creation, must be carefully considered in Fintech activities (Lähteenmäki et al., 2022). Fintech markets can be altered with the help of CC, hence creating new business prospects (Lytras et al., 2020). While considering the comparative potential of the CC, the Fintech revolution in co-innovation has been a topic of conversation (Al Issa & Omar, 2024). Liu (2020) exhibited how machine learning techniques may be used to massive volumes of textual data in a Fintech setting. The discussion concentrates on using social media to enhance marketing endeavors to better comprehend clients and estimate the fiscal yield of businesses. Due to the rise of DL technology and enormous volumes of data, computers can now automatically understand complicated data features, as taught in Fintech knowledge-based marketing (Adam et al., 2021). The Fintech platform uses natural language processing (NLP) to link products and suppliers (Behera et al., 2021). Utilizing digital technology influences customers' opinions of a Fintech service's value (Nguyen et al., 2020). Customer service in online Fintech communications might be extraordinary or deficient (Koponen & Rytsy, 2020). Fintech companies rely substantially on customer service since it minimizes clients' demand for traditional support services (Bone et al., 2015). The relevant research underlines the utility of Robo-advisors for use cases such as customer service. In the near future, Robo-advisors will likely become a fundamental element of the products and services offered to clients via messaging app services (Suhaili et al., 2021). The retail sector has substantially profited from the employment of Robo-advisors (Patil et al., 2023; Rese et al., 2020).

Numerous customer service studies have deemed Robo-advisors, but the cognitive components of personalization and context have been neglected (Behera et al., 2021; Liu et al., 2022; Przegalinska et al., 2019). Notably, the Technology Acceptance Model (TAM) (F. Davis, 1989)and the Information Systems Success Model (ISSM; henceforth referred to as the "D&M model") do not support the employment of Robo-advisors for customer help (DeLone & McLean, 2003). Customers may be dissuaded from making a purchase if there is a lack of trust or satisfaction while shopping online in a customized manner (Abbas et al., 2023). There is also a favorable relationship between the use of personalization and purchasing intent (O. Pappas et al., 2014). Academic research on Fintech personalization is scarce, which calls into doubt their significance (Mhlanga, 2024). Due to the novelty of Robo-advisors as a technology, studies into their acceptability are still in their infancy (Aslam et al., 2023). This study aims to ascertain objectively whether an intelligent Robo-advisor delivers specialized context customer care behind the scenes and beyond publicity. Considering the research question 3 hypothesis development conducted, further process was implemented.

7.1 Hypothesis Development

The success of an "information system" IS relies on information quality, system quality, and service quality, as stated in the D&M paradigm (DeLone & McLean, 2003). To further improve this model, perceived risk has been included as a mediator between the quality components of IS and customer experience, as customers' perceptions of risk can significantly influence their purchase decisions (Liebermann & Stashevsky, 2002). Many researchers have supported this concept, including (Alalwan, 2018; Chau et al., 2007; Mun et al., 2006; Naz et al., 2023; Pillai et al., 2022; Rana et al., 2016; Rana et al., 2012; A. Venkatesh et al., 2003). However, according to Hai and Alam Kazmi (2015), the Technology Acceptance Model (TAM) is insufficient in explaining consumers' behavior towards new technologies. The concept of "perceived trust" has been added to the model to address this limitation. In addition, perceived IT failure risks and the ability of IS to disrupt Fintech have been identified as moderator variables for D&M in the current study. The study discussed nine hypotheses based on the conceptual model, which are depicted in the Figure below. Hypotheses H1 depicted direct effects to H8, whereas the moderating effect was studied in H9.

7.1.1 Model 1

Base model 1 is explained in Figure 8. It includes the D&M Model (2003) and TAM (1989). With the help of perceived trust and perceived risk, it illustrates the customer experience and attitude towards the technology, including the intention to adopt the Robo-advisors.

7.1.2 Model 2

Figure 9 represents the base model 2, UTAUT 2 (2012) (extension of UTAUT 2003), used to identify the behavioral intention and use behavior as a base model 2, which also helps to construct model 3 and model 4 further with the combination of base model 1 and base model 2. The UTAUT2, developed in 2012, is an enhanced version of the initial UTAUT framework launched in 2003. This sophisticated model is crucial for analyzing both the desire to utilize technology and actual usage behavior. It serves as a fundamental Model 2 that improves our comprehension of technology adoption processes and supports the creation of the following models, such as Model 3 and Model 4. The subsequent models combine the original UTAUT framework (Base Model 1) with its successor, UTAUT2 (Base Model 2), providing a more thorough perspective on technological adoption and usage patterns.

7.2 Research Methodology

This study aimed to investigate the perspective of Pakistani Fintech users about the proficiency of Robo-advisors and chatbots, as well as the factors that influence this view. The investigation adhered to the positivist doctrine, which posits the existence of an objective reality that scientific methodologies may elucidate. Theoretical assumptions were formulated using deductive reasoning and subsequently validated using empirical evidence. The sample frame included Pakistani Fintech consumers who had interacted with Robo-advisors or chatbots, capturing a wide range of experiences inside this technological interface. We employed a combination of snowball and purposive sampling techniques to provide a sufficiently large and representative sample of the entire population. Purposive sampling ensured the inclusion of individuals who met the specific requirement of having interacted with Robo-advisors or chatbots. Snowball sampling facilitated the identification of respondents who are typically difficult to identify due to the novelty of the technology. By employing this approach, we successfully obtained 487 legitimate responses to be utilized for subsequent studies.

Data was gathered from November 2023 to January 2024 through the utilization of both printed and online questionnaires to obtain an up-to-date and pertinent perspective on the utilization of financial technology. The primary means of gathering data was administering a questionnaire that followed the positivist research paradigm. The questionnaire aimed to measure the constructs of interest in a quantitative manner. This technology facilitated the collection and objective analysis of quantitative data. The assessment has a distinct chronological context due to its cross-sectional design, capturing a snapshot of the events within the defined span. By employing this approach, we successfully investigated the determinants that impact users' self-perceived proficiency and the current extent of technology adoption through the analysis of specific variables at a given moment.

The study's findings and analyses in the SEM models rely on this methodology, which offers a robust framework for comprehending the aspects that impact the acceptance of chatbots and Robo-advisors among Fintech customers in Pakistan. The study's conclusions are precise representations of the historical and contextual environment since the researchers relied on positivism and logical deduction. This sample size is within the recommended range for usage of the Structural Equation Modeling (SEM) data analysis tool (E. Hair et al., 2006). During the study, minimal interference from the researcher and respondents was maintained to prevent any bias or manipulation. Run the quadratic effect bootstrapping with customer experience and intention to adopt the Robo-advisors. The following graph has been made. It explains the negative effect among the variables. Eventually, it will come to a positive effect.

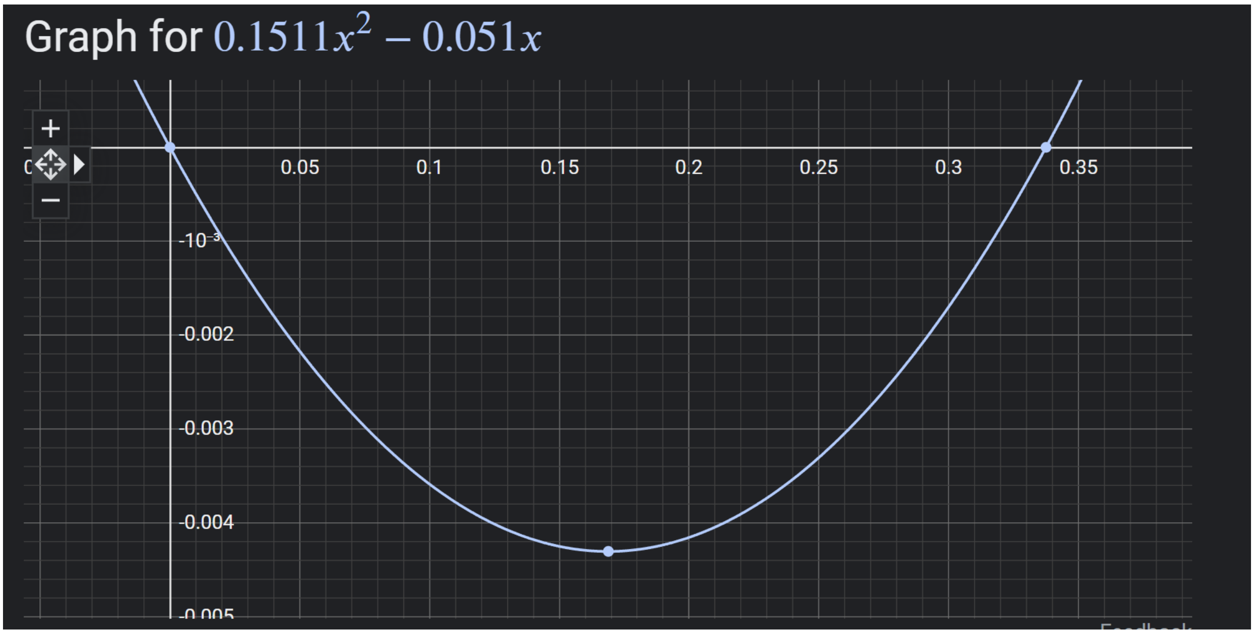

Figure 19 : CE and ITA parabolic curve

The graph depicts a concave upward parabolic curve, indicating a quadratic relationship between CE and ITA rather than a linear one. The examination of this curve indicates the presence of an inflection point when the impact of CE on ITA shifts its direction. More precisely, the function approaches a minimum point where the derivative is zero, indicating the lowest amount of ITA in response to CE. Prior to reaching this minimal degree, an augmentation in CE is linked to a reduction in ITA, which may suggest an initial doubt or insufficient user familiarity to cultivate trust in the Robo advisers' technology. However, the graph shows that above this minimum threshold, further enhancements in CE are associated with a rise in ITA.

This inflection point is of significant significance from an academic and practical standpoint, as it may indicate the level of consumer engagement required for positive attitudes of Robo advisers to start increasing. Comprehending this threshold enables the strategic improvement of client experiences to maximize the adoption rates of Robo advisers. The model's quadratic nature indicates that there is a limit of decreasing returns to advances in CE, beyond which the returns start to climb. The non-linear pattern is crucial for firms aiming to optimize the efficacy of their customer experience initiatives in encouraging the use of Robo advisers.

Another equation has been made with the help of attitude towards technology and intention to adopt the Robo-advisors.

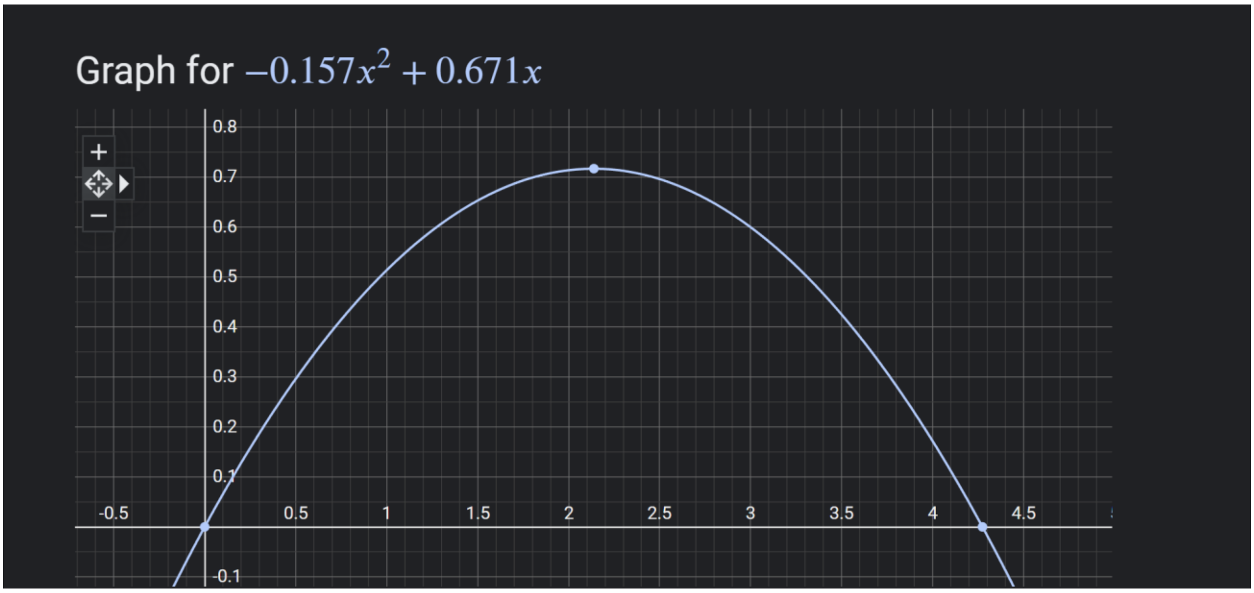

Figure 20 : ATT and ITA parabolic curve

The graph displays a parabolic relationship between two variables, ATT (the independent variable) and ITA (the dependent variable), as described by the quadratic equation −0.157ATT2+0.671ATT. The value of ATT dictates the value of ITA in this equation. The negative coefficient of the ATT2 term implies that the parabola is concave downwards, indicating the existence of a maximum point where ITA achieves its highest value before decreasing as ATT continues to grow. The vertex of the parabola symbolizes the highest point when the amount of ATT is optimized to maximize ITA. Once the peak is reached, every additional increase in ATT leads to a decline in ITA, which is a property that indicates diminishing returns in several real-world situations, such as Technology Acceptance. The graph originates at the origin, indicating that ITA is zero when ATT is 0, highlighting the absence of a fundamental baseline level of ITA without ATT. The exact location of the highest ITA may be found analytically by studying the vertex of the parabola. Comprehending the essence of this graph is essential for making accurate predictions or judgments on the correlation between ATT and ITA, particularly if one intends to maximize results.

7.2.1 Model 1

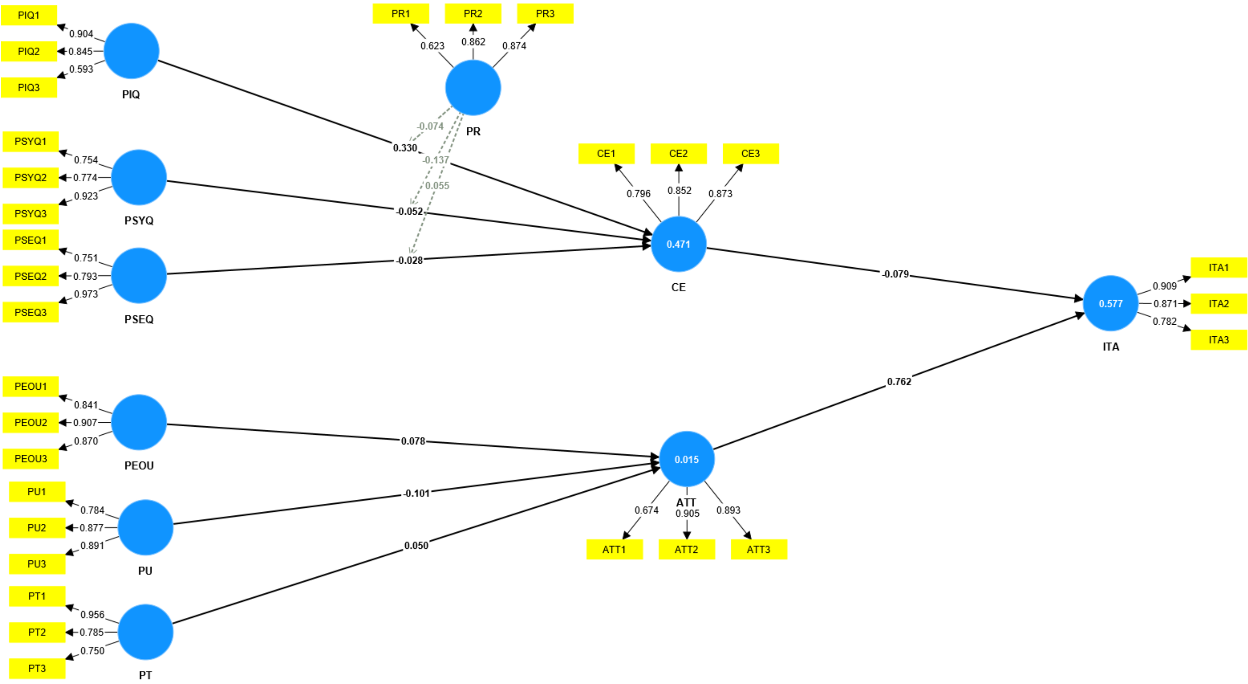

Figure 21 : Model 1 Construct Reliability and Validity

The figure shows the model in Smartpls atmosphere while constructing reliability and validity analysis.

7.2.1.1 Construct Reliability and Validity

Table 13 Construct Reliability and Validity Model 1

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATT	0.764	0.778	0.868	0.690
CE	0.794	0.804	0.879	0.707
ITA	0.818	0.858	0.891	0.732
PEOU	0.846	0.881	0.906	0.762
PIQ	0.705	0.831	0.831	0.628
PR	0.723	0.802	0.834	0.632
PSEQ	0.850	0.871	0.880	0.713
PSYQ	0.787	0.852	0.860	0.673
PT	0.840	0.870	0.873	0.698
PU	0.817	0.868	0.888	0.726

The following metrics are vital for assessing the validity and reliability of research constructs: attitude, consumer engagement, intention to adopt, perceived ease of use, perceived information quality, perceived risk, perceived service quality, Perceived System Quality, perceived trust, and perceived usefulness. Composite Reliability, shown by rho_a and rho_c, quantifies the overall reliability of a construct. Cronbach's alpha assesses the internal consistency of the construct. Average Variance Extracted (AVE) determines convergent validity by measuring the amount of variance collected by a construct from its indicators (Cheung et al., 2024).

Cronbach's alpha values consistently demonstrate a strong and dependable association between the items within each construct, ranging from good to outstanding, thereby confirming the constructs' reliability and validity. The composite reliability ratings (rho_a and rho_c) offer additional evidence of the constructs' reliability and the accuracy of their assessment. Every construct demonstrated sufficient to outstanding internal consistency, reliability, and convergent validity levels, indicating that the study's measurement method is generally strong and reliable. The constructs regularly demonstrate internal consistency inside the model and exhibit strong reliability and validity metrics, indicating their capacity to accurately capture the variance represented by their indicators. However, to ensure accuracy and dependability in assessing these constructs, it is essential to scrutinize or modify the model considering the unusually high composite reliability scores for a few of them.

The inner VIF is consistently below 3.13 for all constructs, indicating the absence of any bias due to common method variance (Nawanir et al., 2016). The model fit value for the Standardized Root Mean Square Residual (SRMR) is 0.08, which satisfies the rule of thumb criterion. The Heterotrait-Monotrait Ratio of Correlations (HTMT) indicates that there are no correlation issues among the indicators across constructs, as it adheres to the rule of thumb for discriminant validity (< 0.90), as stated by Henseler et al. (2015). The Fronell-Larcker criterion states that the square root of the average variance retrieved by a construct must exceed the correlation between the construct and any other construct(Waqar et al., 2024). The cross-loading criteria state that the indicators of a construct should not have larger loadings on the opposing constructions.

7.2.1.2 SEM Model

Table 14 SEM Model 1

Hypothesis	Model 1	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	results
H1	PIQ -> CE -> ITA	-0.026	-0.026	0.01	2.514	0.012	S
H1a	PIQ -> CE	0.33	0.324	0.052	6.385	0	S

H2	PSYQ -> CE -> ITA	0.004	0.003	0.005	0.891	0.373	NS
H3	PSEQ -> CE -> ITA	0.002	0.001	0.004	0.554	0.579	NS
H4	PEOU -> ATT -> ITA	0.038	0.044	0.04	0.951	0.342	NS
H5	PU -> ATT -> ITA	-0.071	-0.074	0.038	1.895	0.058	S at 10%
H6	PT -> ATT -> ITA	0.047	0.039	0.052	0.911	0.362	NS
H7	CE -> ITA	-0.079	-0.079	0.029	2.74	0.006	S
H8	ATT -> ITA	0.762	0.763	0.022	34.528	0	S
H9a	PR x PSEQ -> CE	0.055	0.049	0.04	1.382	0.167	NS
H9b	PR x PIQ -> CE	-0.074	-0.063	0.062	1.198	0.231	NS
H9c	PR x PSYQ -> CE	-0.137	-0.157	0.075	1.818	0.069	S at 10%

The initial model of the study employs snowball and purposive sampling methodologies to ascertain the factors that contribute to the enhanced sense of competence among Robo-advisor users in Pakistan. Participants with a prior understanding of Robo-advisors are participating.

Hypotheses 1 and 1a suggest that PIQ directly impacts CE, which in turn affects ITA (Behera et al., 2021). H1 presents a noteworthy and investigable finding, indicating a negative correlation (-0.026) with a statistically significant outcome ($p = 0.012$). This suggests that enhancing the apparent intelligence of the Robo-advisors may actually decrease its perceived effectiveness. Nevertheless, H1a reveals a robust positive correlation (0.33) with a very significant p-value, indicating that the perceived utility of a Robo-advisor is directly enhanced by its Perceived Information Quality.

Hypotheses 2 and 3 propose that PSYQ and PSEQ, respectively, have an impact on ITA(Ullah et al., 2021) through CE. However, the p-values for these hypotheses are not statistically significant, indicating that they are not supported (NS). Consequently, these qualities have minimal impact on the perceived effectiveness of the Robo-advisors or the likelihood of its utilization by individuals.

The findings of H5 and H7 are captivating. At a significance level of 10%, hypothesis 5 demonstrates that the attitude towards ITA is adversely influenced by perceived utility (PU). This suggests that individuals are less inclined to use Robo-advisors despite their evident usefulness; this might be attributable to several factors, such as a desire for interpersonal interaction or concerns over confidentiality. Users may avoid adopting successful Robo-advisors due to concerns or a perceived lack of control. However, H7 findings indicate that there is a statistically significant negative impact of customer experience (CE) on intention to adopt (ITA) (Abbas et al., 2023; Behera et al., 2021). This suggests that as the perceived effectiveness of the Robo-advisors increases, the desire to adopt it decreases.

In conclusion, it is evident that having a good attitude toward Robo-advisors significantly indicates the desire to adopt them. This is corroborated by the significant positive impact (0.762) demonstrated by H8, which shows the influence of attitude (ATT) on intention to adopt (ITA).

Some hypotheses may have negative beta values due to unaccounted cultural factors, users' illogical responses to intricate technology, or apprehensions over privacy or job stability. In line with most technology acceptance models, positive betas indicate that good perceptions and attitudes towards the technology are usually indicative of the desire to use it. Model 1's findings indicate that individuals' views and intentions about the adoption of Robo-advisors are influenced by their evaluations of the Robo-advisors' intelligence, usefulness, and effectiveness.

7.2.2 Model 2

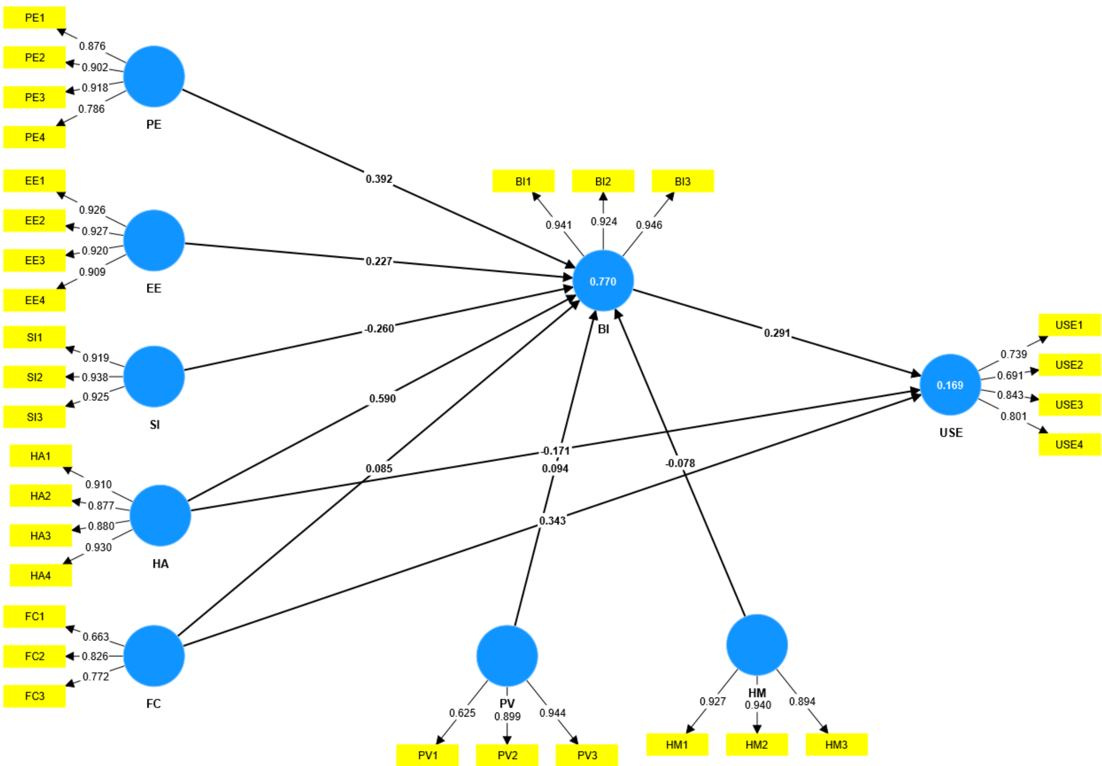

Figure 22 : Model 2 Construct Reliability and Validity

Table 15 Construct Reliability and Validity Model 2

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.930	0.931	0.956	0.878
EE	0.940	0.940	0.957	0.847
FC	0.621	0.613	0.799	0.572
HA	0.921	0.931	0.944	0.809
HM	0.910	0.921	0.943	0.848
PE	0.894	0.897	0.927	0.760
PV	0.815	0.936	0.870	0.697
SI	0.918	0.919	0.948	0.860
USE	0.777	0.806	0.853	0.594

The table displays various research constructs, such as Behavioral Intention (BI), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HA), Performance Expectancy (PE), Perceived Value (PV), Social Influence (SI), and Use Behavior (USE), along with their corresponding reliability and validity metrics. These metrics are used in research to assess measurement models: Cronbach's alpha measures internal consistency, Composite Reliability (rho a and rho c) evaluates overall construct reliability, and Average Variance Extracted (AVE) indicates the amount of variance captured by a construct from its indicators, thus measuring convergent validity.

The figure unambiguously demonstrates that most of the constructs possess outstanding validity and reliability scores. Specifically, the items within each construct (BI, EE, HA, HM, PE, PV, and SI) have strong internal consistency, as seen by their elevated Cronbach's alpha values. Their high composite reliability scores (rho_a and rho_c) demonstrate a significant level of dependability comparable to those of other constructs. The AVE values for these constructs demonstrate strong convergent validity, surpassing the widely accepted requirement of 0.5. This indicates that these structures may account for a significant portion of the variability in the observed variable.

However, the graphic also indicates problematic areas for specific structures. Both USE and FC have notably lower Cronbach's alpha values. However, FC's exceptionally low score of 0.621 suggests that its components have worse internal consistency. The construction may have reliability issues due to the fact that FC's composite dependability is also below the intended range.

All of the constructs have an inner VIF value below 3.13, suggesting the absence of any common method variance bias. The model fit value SRMR is 0.05, which satisfies the rule of thumb requirements. Henseler et al. (2015) found that the Heterotrait– Monotrait ratio of correlation (HTMT) suggests that the indicators do not have any correlations across different constructs, which aligns with the guideline of discriminant validity (< 0.90). In order for a construct to satisfy the Fornell-Larcker criterion, the square root of its average variance extracted should exceed the correlation with all other constructs. Based on the cross-loading criteria, it is expected that the indicators of a particular construct should not have a more substantial influence on other constructs.

7.2.2.1 SEM Model

Table 16 SEM Model 2

Hypothesis	Model 2	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
H1	PE -> BI -> USE	0.114	0.114	0.027	4.151	0	S
H1a	PE -> BI	0.392	0.391	0.037	10.557	0	S
H2	EE -> BI -> USE	0.066	0.067	0.019	3.409	0.001	S
H2a	EE -> BI	0.227	0.228	0.037	6.146	0	S
H3	SI -> BI -> USE	-0.076	-0.076	0.02	3.725	0	S
H3a	SI -> BI	-0.26	-0.259	0.035	7.478	0	S
H4	FC -> BI -> USE	0.025	0.025	0.008	3.059	0.002	S
H4a	FC -> BI	0.085	0.085	0.02	4.159	0	S
H5	HM -> BI -> USE	-0.023	-0.022	0.01	2.232	0.026	S
H5a	HM -> BI	-0.078	-0.078	0.032	2.464	0.014	S
H6	PV -> BI -> USE	0.027	0.028	0.01	2.874	0.004	S
H6a	PV -> BI	0.094	0.097	0.027	3.432	0.001	S
H7	HA -> BI -> USE	0.172	0.172	0.041	4.177	0	S
H7a	HA -> BI	0.59	0.589	0.036	16.396	0	S
H8	FC -> USE	0.368	0.374	0.034	10.883	0	S
H9	HA -> USE	-0.171	-0.171	0.069	2.471	0.013	S
H10	BI -> USE	0.291	0.292	0.067	4.37	0	S

The second model of the study examines the reasons behind the limited adoption of Robo-advisors despite individuals acknowledging their worth. This study uses this model to examine the factors that influence the adoption rates of Robo-advisors (RA) and the intention to utilize them (IU). The data analysis, conducted via Smart PLS, enhances comprehension of the several components involved.

As indicated by H1 and H1a, the results clearly indicate that consumers' propensity to utilize Robo-advisors is greatly impacted by performance expectancy (PE), which has substantial positive effects on both behavioral Intention (BI) and eventual employment. This indicates that individuals are more likely to want to utilize and effectively leverage Robo-advisors when they have confidence in their efficacy. The level of ease in using a product, known as effort expectation (EE), has a positive impact on both behavioral Intention (BI) and actual use (USE) (H2 and H2a). Therefore, user-friendly Robo-advisors tend to be more popular.

On the other hand, H3 and H3a indicate that social influence (SI) has an adverse impact on BI, implying that societal norms or peer pressure may impede the utilization of Robo-advisors. This underscores the fact that user acceptance may encounter impediments stemming from social challenges beyond their jurisdiction. On the other hand, facilitating conditions (FC) have been shown to have a small but favorable impact on behavioral Intention (BI) and user experience (USE) (H4 and H4a). This indicates that providing the necessary infrastructure and support might be somewhat beneficial for adoption.

The presence of hedonic motivation (HM) has a detrimental impact on both behavioral Intention (BI) and user experience (USE) (H5 and H5a). This finding is intriguing as it suggests that the limited adoption of Robo-advisors is not due to their high level of enjoyment during usage. This might be attributed to a defect in the user interface's design. Users prefer cost-effectiveness, as seen by the positive impact of pricing value (PV) on both behavioral Intention (BI) and user experience (USE) (H6 and H6a).

There exists a contradiction in the role of habit (HA), whereby it has a positive influence on behavioral intention (H7 and H7a) yet has a detrimental impact on actual usage (H9). This suggests that the acceptance of Robo-advisors is not certain, even among those who have previously used similar technologies. There is a strong correlation between enabling conditions and USE (H8), emphasizing the importance of Robo-advisors' user-friendly interface and assistance in determining their actual usage (Nourallah, 2023). The positive association between behavioral Intention and use (H10) demonstrates that consumers' intent to utilize is a significant determinant in the adoption of Robo-advisors.

To summarize, Model 2 demonstrates that there are several factors that impact the acceptability of Robo-advisors by users. Practical performance and favorable circumstances contribute to the increase in adoption. Conversely, social factors and pleasurable motivation might impede its progress. The findings obtained from these studies can provide valuable guidance for future endeavors aimed at enhancing the design and advertising of Robo-advisors.

7.2.3 Model 3

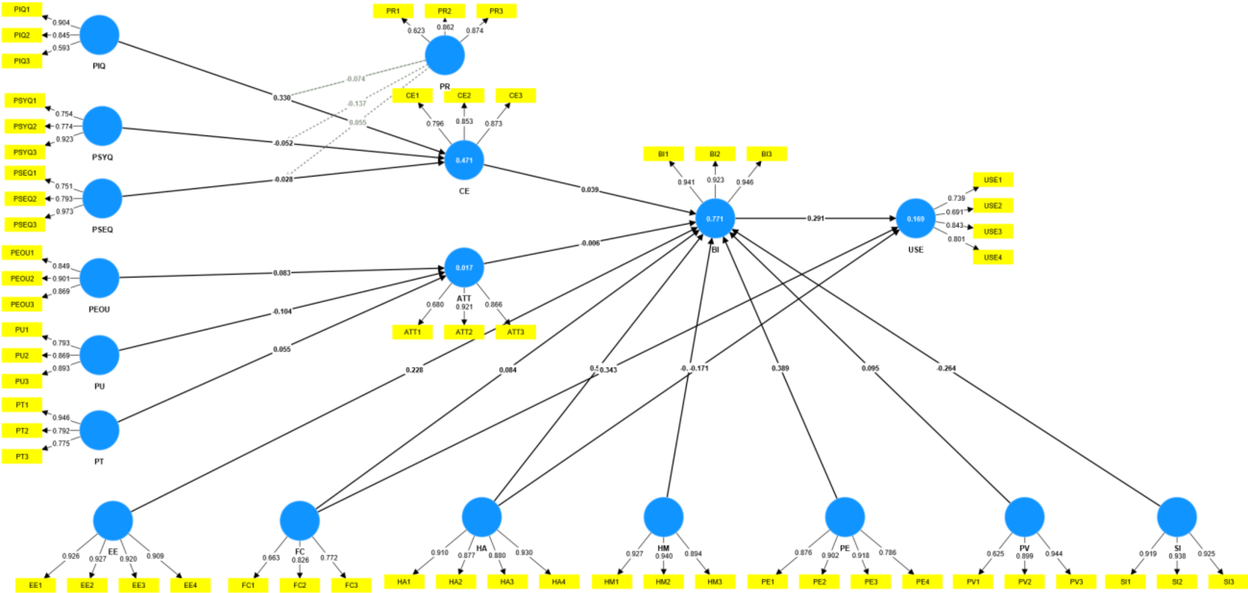

Figure 23 : Figure 19 Model 3 Construct Reliability and Validity

Table 17 Construct Reliability and Validity Model 3

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATT	0.764	0.837	0.866	0.686
BI	0.930	0.931	0.956	0.878
CE	0.794	0.804	0.879	0.707
EE	0.940	0.940	0.957	0.847
FC	0.621	0.613	0.799	0.572
HA	0.921	0.931	0.944	0.809
HM	0.910	0.921	0.943	0.848
PE	0.894	0.897	0.927	0.760
PEOU	0.846	0.869	0.906	0.763
PIQ	0.705	0.830	0.831	0.628
PR	0.723	0.802	0.834	0.632
PSEQ	0.850	0.850	0.880	0.713
PSYQ	0.787	0.841	0.860	0.673
PT	0.840	0.853	0.878	0.708
PU	0.817	0.854	0.889	0.728
PV	0.815	0.936	0.870	0.697

SI	0.918	0.919	0.948	0.860
USE	0.777	0.806	0.853	0.594

This table presents a comprehensive summary of the reliability and validity metrics for different constructs in a research study. The constructs encompassed in this list are attitudes, behavioral intentions, consumer engagement, effort expectancy, facilitating conditions, hedonic motivation, habits, performance expectancy, perceived ease of use, perceived information quality, perceived risk, perceived service quality, Perceived System Quality, perceived trust, perceived usefulness, perceived value, social influence, and use behavior. Several metrics are used to assess the quality of the data. These include Cronbach's alpha, which evaluates internal consistency; Composite Reliability, which measures the reliability of the constructs; and the Average Variance Extracted (AVE), which tests for convergent validity by comparing the construct's variance capture to the measurement error variance.

The constructions have good reliability and internal consistency, as seen by their high composite reliability scores and Cronbach's alpha. The measurements in this study demonstrate exceptional dependability, as indicated by the remarkably high values of BI, EE, HA, and SI. Furthermore, their AVE values are above the threshold of 0.5, indicating robust convergent validity and demonstrating that the constructs explain a significant portion of the observed variables' variability. The rigorous criteria of validity and consistency demonstrate the reliability of the constructs in accurately assessing the phenomena of interest and lend credibility to the study's measurement approach.

In order to ensure the accuracy and reliability of the model for all constructs, it may be imperative to address the specific deficiencies identified in FC, PSEQ, PSYQ, and PT. All of the constructs have an inner VIF value below 3.13 (Shahzad et al., 2021), suggesting the absence of any common method variance bias. The SRMR model fit value of 0.053 satisfied the specified conditions. Henseler et al. (2015) found that the Heterotrait– Monotrait ratio of correlation (HTMT) suggests that the indicators do not have any correlations with other constructs, which aligns with the guideline of discriminant validity (< 0.90). In order for a construct to satisfy the Fronell-Larcker criterion, the square root of its average variance must exceed the correlation between all other constructs. Based on the cross-loadings criteria, it is expected that the indicators of a particular construct should not have a greater influence on other constructs.

7.2.3.1 SEM Model

Table 18 SEM Model 3

Hypothesis	Model 3	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
H1	BI -> USE	0.291	0.292	0.067	4.37	0	S
H2	EE -> BI	0.228	0.229	0.037	6.164	0	S
H3	FC -> BI	0.084	0.085	0.02	4.173	0	S
H4	FC -> USE	0.343	0.349	0.035	9.738	0	S
H5	HA -> BI	0.59	0.588	0.036	16.346	0	S
H6	HA -> USE	-0.171	-0.171	0.069	2.471	0.013	S
H7	HM -> BI	-0.074	-0.074	0.032	2.27	0.023	S
H8	PE -> BI	0.389	0.389	0.037	10.429	0	S
H9	PIQ -> CE	0.33	0.324	0.052	6.373	0	S
H10	PR -> CE	0.455	0.462	0.059	7.756	0	S
H11	PU -> ATT	-0.104	-0.113	0.05	2.067	0.039	S
H12	PV -> BI	0.095	0.098	0.028	3.408	0.001	S
H13	SI -> BI	-0.264	-0.263	0.035	7.451	0	S
H14	PR x PSYQ -> CE	-0.137	-0.157	0.075	1.815	0.07	S
H15	HM -> BI -> USe	-0.021	-0.021	0.01	2.096	0.036	S
H16	FC -> BI -> USe	0.025	0.025	0.008	3.075	0.002	S
H17	HA -> BI -> USe	0.172	0.172	0.041	4.173	0	S
H18	PE -> BI -> USe	0.113	0.113	0.027	4.162	0	S
H19	PV -> BI -> USe	0.028	0.028	0.01	2.866	0.004	S
H20	EE -> BI -> USe	0.066	0.067	0.019	3.411	0.001	S
H21	SI -> BI -> USe	-0.077	-0.077	0.021	3.722	0	S

This research primarily focuses on Robo-advisors, whereas Model 3 delves into the intricacies of user adoption and engagement with technology in a broader sense. Model 3 conducts studies to examine many factors that influence users' motivation or discouragement when using automated advising services. These factors include behavioral intention to use (BI), actual use (USE), effort expectancy (EE) (An et al., 2023), and others.

A high path coefficient, which signifies a direct correlation between users' intentions and subsequent actions, suggests that behavioral intention is a reliable predictor of technology usage. The research was done using Smart PLS software, which allows for the implementation of Structural Equation Modeling (SEM). The confirmation of the anticipation of effort as a significant predictor of intention and actual usage underscores the need to design user-friendly interfaces to promote higher rates of adoption.

When enabling factors, such as the necessary resources and support, are taken into account, there is a clear and statistically significant correlation between intention and utilization. This implies that individuals are more inclined to effectively utilize Robo-advisors when equipped with appropriate resources (Cheng, 2023). Interestingly, the presence of a habit encourages the desire to use, but at the same time, it obstructs the actual usage. This implies that there can be a discrepancy between users' established routines and their willingness to adopt new technologies into such routines.

There is a negative relationship between both intention and usage and hedonic motivation, which is typically associated with the pleasure or satisfaction derived from using something. Given their utilitarian nature, this unexpected outcome suggests that the pleasure component may have less significance in the context of Robo-advisors.

It is important to note that customers' views on the competence and intelligence of Robo-advisors have a significant role in their decision to use them. The expectations of how well the technology would perform and how intelligent it is thought to be are both positively linked to the effectiveness and usage of Robo-advisors. Individuals may exhibit reluctance to employ Robo-advisors owing to the influence of their peers or other social factors, as social influence is commonly seen as exerting an adverse effect. The impact of perceived risk on Robo-advisors' efficacy is ambiguous. On one hand, it suggests that a moderate level of risk is linked to successful utilization. On the other hand, its interaction with psychological attributes can detrimentally affect efficacy, implying an intricate connection between users' risk profiles and their perceptions of technology. Ultimately, the price of the technology is strongly correlated with both intention and usage, demonstrating that economic considerations significantly impact consumers' decision-making.

In summary, Model 3 encompasses all the crucial factors that influence Robo-advisors' acceptability. The text emphasizes the importance of user-friendliness, support systems, and performance dependability. Additionally, it acknowledges potential variables that may cause user resistance, such as habit inertia, societal attitudes, and hedonic incentives. These findings provide a valuable basis for enhancing user engagement and promotion of Robo-advisors.

7.2.4 Model 4

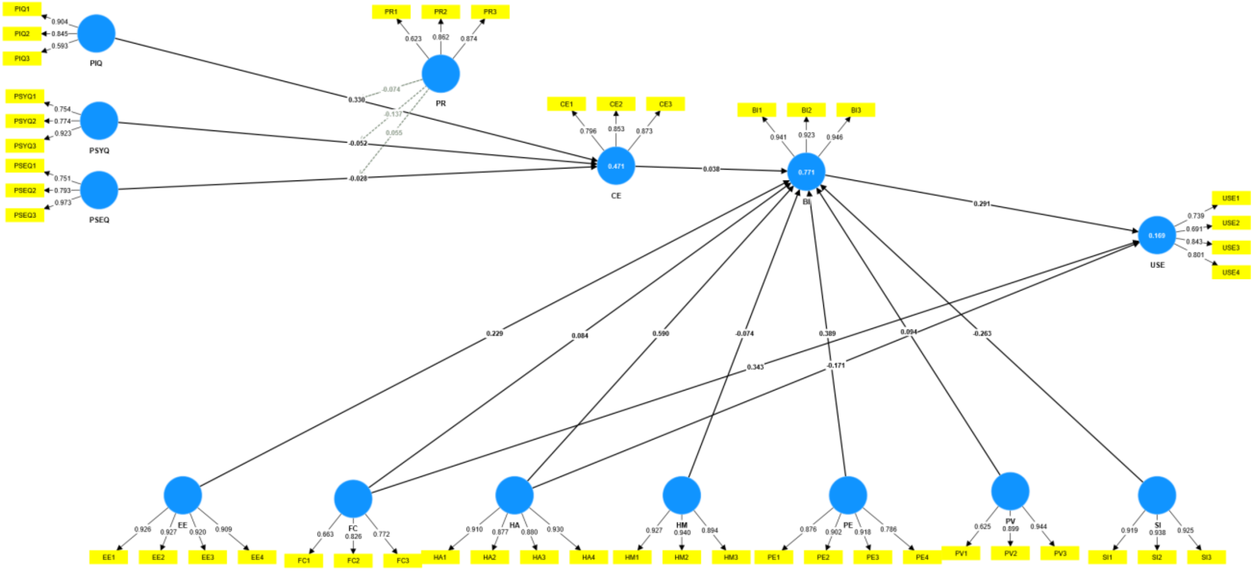

Figure 24 : Model 4 construct Reliability and Validity

Table 19 Construct Reliability and Validity Model 4

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.930	0.931	0.956	0.878
CE	0.794	0.804	0.879	0.707
EE	0.940	0.940	0.957	0.847
FC	0.621	0.613	0.799	0.572
HA	0.921	0.931	0.944	0.809
HM	0.910	0.921	0.943	0.848
PE	0.894	0.897	0.927	0.760
PIQ	0.705	0.830	0.831	0.628
PR	0.723	0.802	0.834	0.632
PSEQ	0.850	0.854	0.880	0.713
PSYQ	0.787	0.832	0.860	0.673
PV	0.815	0.936	0.870	0.697
SI	0.918	0.919	0.948	0.860
USE	0.777	0.806	0.853	0.594

The table includes various constructs such as Behavioral Intention (BI), Customer Experince (CE), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HA), Habit (HM), Performance Expectancy (PE), Perceived Information Quality (PIQ), Perceived Risk (PR), Perceived Service Quality (PSEQ), Perceived System Quality (PSYQ), Perceived Value (PV), Social Influence (SI), and Use Behavior (USE). Its corresponding reliability and validity measures accompany each construct. Below are certain metrics that should be taken into consideration: Cronbach's alpha assesses the internal consistency of the items within each construct. Composite Reliability evaluates the overall reliability of the constructs. Average Variance Extracted (AVE) measures the convergent validity of a construct by quantifying the extent to which it captures variance from its indicators.

The validity and reliability of the constructs exhibit variability. Constructs such as BI, EE, HA, HM, and SI have excellent composite reliability scores and Cronbach's alpha, suggesting that they are consistently and reliably measured. Furthermore, their Average Variance Extracted (AVE) values are above the 0.5 threshold, indicating strong convergent validity and a substantial explanation of the observed variance in the variables. This demonstrates the robustness of the measurement model in accurately and consistently measuring the constructs, enabling them to effectively capture the phenomena they are intended to reflect.

All of the constructs have an inner VIF below 3.13 (Alqudah et al., 2023), suggesting the absence of any common method variance bias. The SRMR model fit value of 0.056 (Wu et al., 2023) satisfied the requirements for adequacy. Henseler et al. (2015) found that the Heterotrait–Monotrait ratio of correlation (HTMT) suggests that the indicators do not exhibit any cross-construct correlations, therefore supporting the discriminant validity rule of thumb (< 0.90). In order for a concept to satisfy the Fornell-Larcker criterion, the square root of the average variance it captures must exceed the correlation with all other constructs. Based on the cross-loading criteria, it is expected that the indicators of a particular construct should not have a greater influence on the other constructs.

7.2.4.1 SEM Model

Table 20 SEM Model 4

Hypothesis	Model 4	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
H1	BI -> USE	0.291	0.292	0.067	4.37	0	S
H2	EE -> BI	0.229	0.23	0.037	6.196	0	S
H3	FC -> BI	0.084	0.084	0.02	4.142	0	S
H4	FC -> USE	0.343	0.349	0.035	9.738	0	S
H5	HA -> BI	0.59	0.588	0.036	16.411	0	S
H6	HA -> USE	-0.171	-0.171	0.069	2.471	0.013	S
H7	HM -> BI	-0.074	-0.074	0.032	2.271	0.023	S
H8	PE -> BI	0.389	0.388	0.037	10.476	0	S
H9	PIQ -> CE	0.33	0.324	0.052	6.373	0	S
H10	PR -> CE	0.455	0.462	0.059	7.756	0	S

H11	PV -> BI	0.094	0.097	0.028	3.403	0.001	S
H12	SI -> BI	-0.263	-0.263	0.035	7.495	0	S
H13	HM -> BI -> USE	-0.021	-0.021	0.01	2.097	0.036	S
H14	PE -> BI -> USE	0.113	0.113	0.027	4.164	0	S
H15	PV -> BI -> USE	0.027	0.028	0.01	2.861	0.004	S
H16	FC -> BI -> USE	0.024	0.025	0.008	3.062	0.002	S
H17	EE -> BI -> USE	0.067	0.067	0.019	3.416	0.001	S
H18	HA -> BI -> USE	0.172	0.172	0.041	4.174	0	S
H19	SI -> BI -> USE	-0.077	-0.077	0.021	3.724	0	S

The factors that affect the adoption and usage of Robo-advisors are examined in more detail in Model 4. This study expands upon previous models by examining the impact of various social and psychological factors on users' behavior intention (BI) and technology usage (USE), as well as exploring the interrelationships between these variables.

According to the findings of H1, the model validates that behavioral intention plays a crucial role in influencing the actual usage. Examining the factors that affect intentions is essential since a user's inclination to use Robo-advisors significantly influences their actual usage.

Effort expectation (EE) is a significant determinant in the context of behavioral Intention (BI), specifically in relation to hypotheses H2 and H17. This underscores the crucial role of ensuring that Robo-advisors are user-friendly and easy to use in order to promote user engagement. The positive impacts of facilitating conditions (FC) on behavioral Intention (H3) and direct usage (H4 and H16) strongly support the notion that user adoption is dependent on the necessary resources and help required for the process.

Habit (HA) is contradictory (H5, H6, and H18). While consumers' behaviors significantly predict their inclination to utilize Robo-advisors, this has a beneficial impact on behavioral Intention (BI) but a negative impact on user experience (utilize). This suggests that consumers' resistance to change or their inability to integrate Robo-advisors into their daily routines are hindering their use of the technology, even when they have a strong desire to utilize it frequently.

The reason why people are not interested in using Robo-advisors is due to a lack of inherent incentives, specifically hedonic motivation. This lack of motivation has negative effects on behavioral Intention, as indicated by hypotheses H7 and H13. Users anticipate an enjoyable and engaging encounter, suggesting that there may be potential for enhancing the user experience.

The findings from studies H8 and H14 support the notion that performance expectancy (PE) is a reliable indicator of behavioral intention (BI), providing support for the premise that customers' decision to use Robo-advisors is heavily influenced by their perception of the technology's effectiveness.

The effectiveness of the Robo-advisors with respect to customer experience (CE) is directly connected to both the perceived risk (PR) and Perceived Information Quality (PIQ), as shown in hypotheses 9 and 10. Users are more inclined to see Robo-advisors as successful if they regard them as intelligent and if they believe that the risks associated with them can be controlled.

The importance of cost-effectiveness in the adoption process is emphasized by the direct correlation between price value (PV) and behavioral Intention (H11 and H15). Peer pressure and cultural norms are instances of social pressures that may discourage customers from using Robo-advisors, as seen by the adverse impacts of social influence (SI) on both behavioral intention (BI) and use (USE) (H12 and H19, respectively).

In summary, Model 4 restates several findings from prior models, emphasizing the intricate variables that influence the adoption of Robo-advisors. The text emphasizes the adverse consequences of societal influence and the pursuit of pleasure while underscoring the significance of behavioral objectives, user-friendliness, and the specific conditions for application as crucial factors. An effective approach to address the issue of resistance, as indicated by the inverse relationship between habitual usage and actual use, is to integrate Robo-advisors seamlessly into consumers' daily routines. In order to effectively promote Robo-advisors and ensure their integration into the financial routines of potential clients, developers and marketers must possess a comprehensive understanding of these intricacies.

7.3 Models Comparison

Table 21 Models Comparison

Criterion	Model 1	Model 2	Model 3	Model 4

PLS Based Criterion	r2	0.484	0.77	0.771	0.771
	Adj r2	0.482	0.767	0.767	0.768
Asymptotically efficient criterion	AIC	-317.2238542	-700.7332255	-698.8552332	-700.8552332
	AICc	171.8591334	-211.355867	-209.2994438	-211.3930484
	AICu	-314.2145758	-692.6667885	-688.7511364	-691.771032
	FPE	0.521324011	0.237194617	0.238111735	0.237135498
	Mallow's Cp	39.28215768	19.26315789	27.64	19.13157895
Asymptotically Consistent criterion	BIC	-304.6590618	-667.2271125	-656.972592	-663.1608561
	GM	538.84695	539.7692709	556.5226412	543.8259561
	HQ	-312.2879265	-687.5707517	-682.4021409	-686.0474502
	HQc	-312.1744833	-686.9593791	-681.4812207	-685.2892871
PLS Predict	Q^2predict	-0.003	0.763	0.762	0.762

The table presents a comparative study of four unique models in Partial Least Squares (PLS) regression, evaluated based on several criteria.

The table presents the adjusted R-squared and coefficient of determination (R-squared) for criteria based on Partial Least Squares (PLS). These statistics indicate the proportion of the dependent variable's variability that may be forecasted based on the independent variables. The r2 values of Models 2, 3, and 4 are significantly higher, around 0.77, indicating that they account for approximately 77% of the variability. In contrast, Model 1 has the lowest r2 value, 0.484, implying that it explains just about 48.4% of the variance. Model 1 has an adjusted r2 value of 0.482, while the other three models provide adjusted r2 values ranging from around 0.767 to 0.768. These results suggest that the models remain robust even when accounting for the number of predictors and sample size. The modified R-squared values exhibit a slight decrease but maintain a consistent trend.

Evaluation of model fit is conducted using many metrics based on the asymptotically efficient criterion. The metrics encompassed are Mallow's C, Final Prediction Error (FPE), unbiased AIC (AICu), corrected AIC (AICc), and Akaike Information criteria (AIC). Model 1 exhibits substantially higher (undesirable) AIC, AICc, and AICu values in comparison to the other models, suggesting a poorer fit of the model when accounting for the number of parameters. Once again, Models 2, 3, and 4 demonstrate superior performance compared to Model 1 in terms of prediction error, as assessed by FPE and Mallow's C. Smaller numbers suggest more predictive capability.

Bayesian Information Criteria (BIC), Goldfeld-Quandt Statistic (GM), and Hannan-Quinn Criteria (HQ and HQc) are all elements of the asymptotically consistent criterion (Sharma et al., 2019). Models 2, 3, and 4 provide a stronger fit to the data compared to Model 1, as indicated by their lower BIC values based on these criteria. The data's equal variance may be compromised due to the greater GM value of Model 3, indicating a potential issue with homoscedasticity. Quantiles greater than 0 indicate that the model is predictive for the dependent variable, and the PLS Predict criteria, Q^2predict, assesses this predictive relevance. Models 2, 3, and 4 demonstrate strong predictive abilities, as evidenced by their Q^2predict values of about 0.76. In contrast, Model 1 has a negative Q^2predict value, indicating a lack of predictive relevance.

Models 2, 3, and 4 exhibit much better fit and predictive capacity across all criteria when compared to Model 1. However, Model 2 only shows the UTAUT and UTAUT 2, whereas 3 shows TAM along with the UTAUT, which is theoretically not as strong as TAM and UTAUT 2, which somehow overlap. Model 4 seems a better option than the remaining as it overcomes the theoretical overlapping bias and also adheres to the strong R2 and predicting as well. Considering the study could look at the demographics further with respect to model 4.

7.4 Demographical Explanation

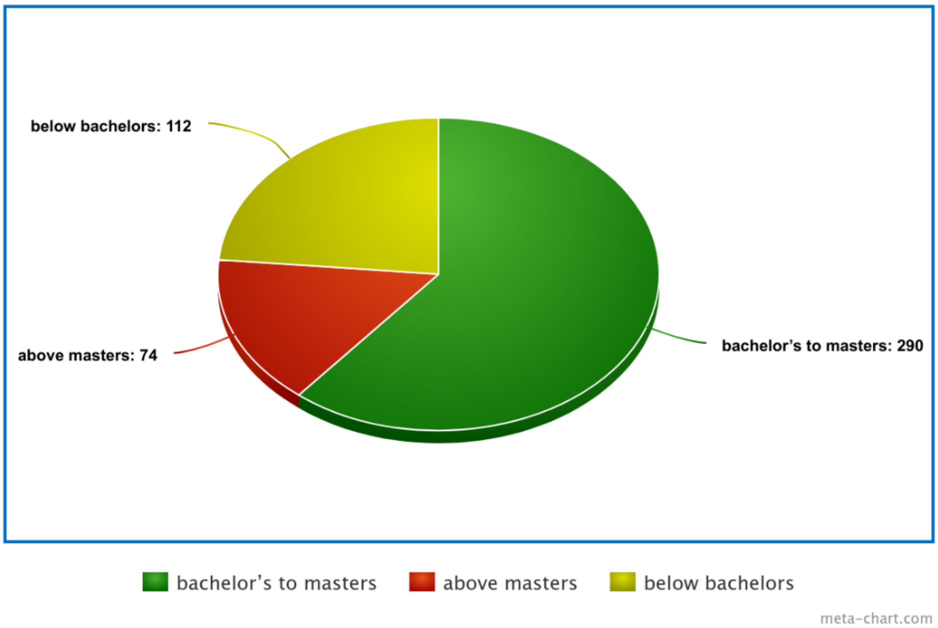

Figure 25:Educational Level Significance

Three groups of **educational level** were made, and the most significant group among others was bachelor's to master in which 290 respondents were part of the study, whereas other two groups below bachelor (112) and above master (74) were not significant. **Income level** 3 (62 respondents) was significant with PIQ, and Income level 4 (101 respondents) was significant with PV, PE, and HA, whereas other income levels remain insignificant.

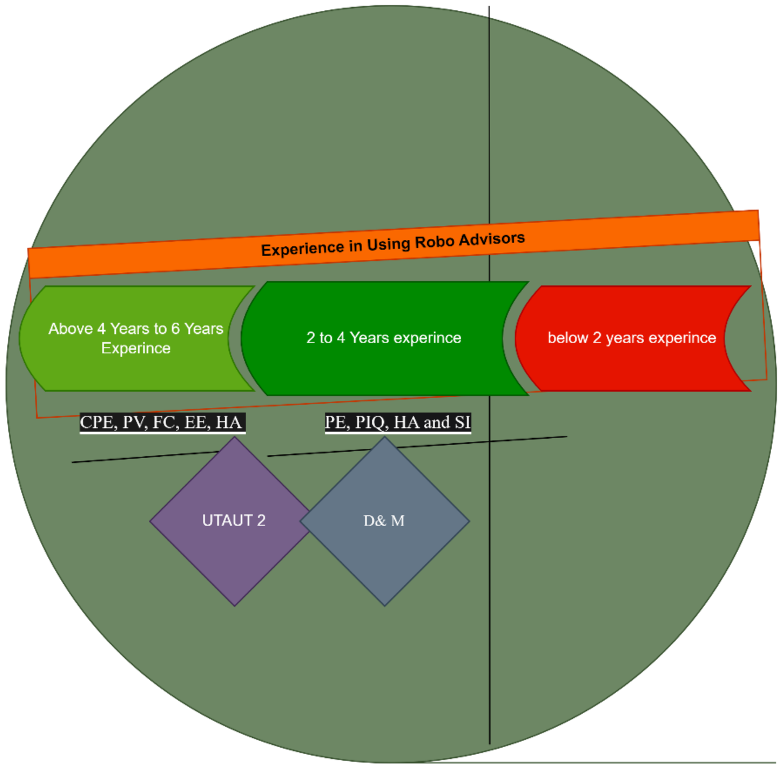

Figure 26:Experience Level Significance

Years of experience have been divided into three groups. Group 1 (4-to-6-years' experience), 133 respondents, was significantly effective with PE, PV, FC, EE, and HA with respect to users, and group 2 (2 to 4 years experience), including 231 respondents was significant for PE, PIQ, HA, and SI. In contrast, group 3, which just started using within 2 years, was not a significant group for the determinants. It can be concluded that more experience can generate more significance for users. Also, more experienced users do not follow SI. Only **Married users** (295 respondents) were significantly affected by PE, FC, EE, and HA positively towards using Robo-advisors and negatively towards SI. **Gender:** female users (98 respondents) have a significant effect of PE, HA, and SI, whereas Male users (389 respondents) have the significance of PE, PV, FC, EE, HA, and SI. **The level of savings** was divided into four groups. In Group 1 (below 10% of income), 114 respondents were significantly affected by PE, HA, and SI, whereas in Group 3 (20% to 30%), 78 respondents had HA significance, and in Group 4 (more than 30%) 92 respondents were having the significance of PE.

7.5 Conclusion and Discussion

An extensive analysis of the impacts of various theoretical frameworks on users' inclination to adopt chatbots and Robo-advisors provides insights into the mechanisms by which customers embrace and utilize these technologies. The first iteration of the Technology Acceptance Model (TAM) and the DeLone and McLean Model of Information System Success serve as fundamental frameworks for comprehending user adoption. Nevertheless, when employed in intricate systems like chatbots and Robo-advisors, it appears that Model 1 is less comprehensive in elucidating user intentions. To accurately capture user adoption behavior, models must incorporate a wider range of factors, a necessity driven by the progressive evolution of technology.

Model 2, in the context of Robo-advisors, utilizes UTAUT2 (Unified Theory of Acceptance and Use of Technology 2), which provides a more comprehensive and stronger framework. This theory incorporates novel factors, such as habit and hedonic incentives. UTAUT2's findings indicate that user intention is influenced by several factors, such as the perceived utility and ease of use suggested by the original TAM, and more abstract factors like enjoyment and habitual convenience. This underscores the intricate aspect of technology adoption, which is greatly shaped by behavioral and emotional traits.

In order to gain a deeper understanding of the increasing popularity of Robo-advisors, Model 3 incorporates the UTAUT2, TAM, and the D&M Model. The combination of the core elements of UTAUT2 with the system and information quality aspects of the D&M Model covers a wider spectrum of issues. Model 3's efficacy suggests that a comprehensive understanding of the factors driving user acceptance of advanced automated financial advisers may be achieved by employing an interdisciplinary approach that incorporates several theoretical perspectives.

The fourth model, which excludes the TAM components, integrates the UTAUT2 with the D&M Model. While the core parts of the Technology Acceptance Model (TAM) are important, the additional variables from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the DeLone and McLean Model (D&M Model) significantly enhance the understanding of user intention, as demonstrated by the effectiveness of this model (Bayastura et al., 2022). Model 4's robust prediction capacity suggests that the user's purpose in using Robo-advisors is multifaceted and should be comprehended from several perspectives, such as user experience, system performance, and the unique advantages of these technologies. Based on these findings, it is evident that we must consider not only user intent as assessed by conventional models but also the wider consequences and the ever-changing nature of user-technology interactions.

By utilizing the findings of the SEM model and considering the study subject of the factors that contribute to Robo-advisors users' sense of competence, we can generate a comprehensive discussion and draw a conclusive statement.

From the SEM analysis, it is evident that Behavioral Intention (BI) is a reliable indicator of actual Use, as demonstrated by all of the models. This finding emphasizes the significance of user intent in the adoption of Robo-advisors and chatbots. The anticipated effectiveness and ease of use of Robo-advisors play a critical role in influencing user intentions since parameters such as Effort Expectancy (EE) and Performance Expectancy (PE) consistently have a significant positive impact on behavioral Intention (BI). Given the robust positive associations shown between Hedonic Motivation (HA) and BI across all models, it appears that enhancing enjoyment and novelty is crucial for fostering individuals' sense of competence.

A notable paradox is the adverse impact of hedonic motivation on practical utilization, as evidenced by the models. Although Robo-advisors possess the capacity to provide amusement, their ability to retain user engagement is not guaranteed. This phenomenon might be attributed to either the novelty effect or the lack of integration into individuals' daily routines. Perceived ability alone may not suffice to overcome preexisting habits or social impediments, as the detrimental effects of Habit (HM) and Social Influence (SI) on BI indicate potential resistance to change and the influence of social norms on technology adoption.

Ensuring that users have access to the necessary resources and derive benefits from Facilitating Conditions (FC) and Perceived Value (PV) is of utmost importance since these aspects positively impact behavioral Intention (BI) and Use. Upon comparing the four models, it becomes evident that each one integrates different components that enhance our understanding of user adoption. The inclusion of system quality and information quality in the D&M model results in a comprehensive set of factors that influence perceived competence and subsequent technology utilization.

In essence, SEM models demonstrate that other factors outside the basic functioning of Robo-advisors have an impact on how competent they are considered to be. Key determinants encompass user pleasure, perceived usability, anticipated efficacy, and accessible support. In order to enhance consumer acceptability and boost perceived expertise, designers and developers of chatbots and Robo-advisors must consider these intricate dynamics. In addition, it may be necessary to adopt strategies aimed at mitigating the adverse consequences of habit and social pressure, with the ultimate goal of converting positive perceptions into consistent practice. The models' insights can direct targeted efforts to enhance user adoption of automated advice services and shed light on the intricate processes involved in their acceptance.

7.6 Future Direction and Limitations

The findings of this study present several promising prospects for future investigation. Subsequent investigations might focus on the strategies employed by Robo-advisor users to maintain their involvement over an extended period. This research would particularly emphasize the conversion of initial satisfaction into sustained usage while considering the intricate connection between enjoyment and practical utilization. Conducting longitudinal studies that track users over time might be beneficial in uncovering the underlying reasons for the negative impact of hedonic incentives on actual usage. Additional investigation is necessary to explore change management strategies and the integration of emerging technologies into current systems and societal norms, as the acceptance of Robo-advisors is influenced by established social behaviors and expectations.

The objective of future research might be to enhance perceived competence and acceptance by providing individualized Robo-advisors experiences tailored to each user's specific requirements and preferences. Another intriguing subject is the utilization of AI to enhance the adaptability and intelligence of Robo-advisors, hence enhancing their ability to acquire knowledge and deliver an enhanced user experience. Given the diverse impact of social elements on different civilizations, doing cross-cultural research can provide insights into how cultural differences influence the adoption of chatbots and Robo-advisors.

An important drawback is the reliance on self-reported data, which is vulnerable to biases such as the tendency to overestimate one's own usage or intentions. The study's models may fail to account for some variables that influence the adoption of Robo-advisors and the perception of their competence, such as variations in technology literacy or specific use cases in different sectors, despite their overall reliability. Although statistical data suggests that hedonic motivation negatively impacts usage, our discovery implies that other unmeasured factors may have a stronger influence on the relationship between enjoyment and sustained involvement. Finally, doing future research utilizing longitudinal designs would be advantageous, as the cross-sectional study lacks the ability to establish causal relationships over time. To enhance our understanding of Robo-advisors' adoption and develop user-centric conversational bots, it is imperative to tackle these limitations in future studies.

8. Conclusion and Discussion

The objective of this thesis was to examine the factors contributing to the limited adoption of chatbots and Robo-advisors in the financial technology sector, as well as their efficacy in addressing critical concerns such as data protection, security, and trust. This study revealed key factors that influence the acceptance of chatbots and Robo-advisors. It was conducted through a comprehensive analysis using NVivo software and extensive interviews with workers and management in the Fintech industry. Robo Advisors have the capacity to revolutionize the financial services sector by offering convenient, effective, and customized guidance. However, gaining widespread acceptance remains challenging due to concerns around privacy, security, and trust. To enhance the confidentiality and integrity of customer data, it is essential to conduct regular security audits and updates and use multi-layered security measures. The study suggests that enhancing the security framework of chatbots and Robo-advisors necessitates continuous focus, novel concepts, and collaborations with financial institutions. Furthermore, it became evident that the implementation of real-time monitoring, ongoing technological advancements, and the utilization of state-of-the-art encryption technologies were essential in building user trust and ensuring the secure operation of these systems.

The interviews were deliberately executed in two geographic phases. Phase 1 captured baseline attitudes in Pakistan—an emerging FinTech market whose respondents were already familiar with Robo-advisors but had limited exposure to fully fledged Robo-advisors—while Phase 2 shifted the lens to Hungary, a digitally advanced EU member-state where real-time payments and PSD2-driven open banking are already mainstream. Analyzing the Hungarian corpus in isolation (as reported in Section 5) allowed us to surface context-specific drivers—most notably the "trust triad" of data-security guarantees, privacy transparency, and institutional endorsement—but comparing these Hungarian narratives with the earlier Pakistani set demonstrated that concerns over algorithmic opacity and fear of cyber-fraud are not confined to advanced markets; rather, they intensify when national regulators signal tighter consumer-protection standards, as is the case in the EU. Including both phases strengthens the external validity of our conclusions while highlighting the moderating role of regulatory maturity in shaping user expectations.

Regarding financial technology advancements such as chatbots and Robo-advisors, the key topics of discussion are privacy, security, and trust. The empirical data collected from Fintech professionals through qualitative interviews provides a comprehensive understanding of the many difficulties and potential solutions. The research indicates that Robo-advisors are not now prevalent despite their considerable potential and excellent technological capabilities. The primary reason for this is mostly due to individuals' concerns over their security and privacy. This study contributes to existing knowledge by demonstrating that enhancing the perceived trustworthiness and security of chatbots and Robo-advisors is not just a technological challenge but also a behavioral and psychological one. While it is crucial to enforce robust security measures such as encryption and multi-layered protocols, it is as necessary to focus on enhancing the reliability and proficiency that consumers perceive. This entails monitoring new legislation, regularly upgrading systems, and consistently allocating resources to research and development.

To enhance the perceived competence and acceptability of chatbots and Robo-advisors, the study emphasizes the need for intuitive design, user-friendly navigation, and the integration of feedback-driven service upgrades to create a pleasant user experience. To navigate the challenging realm of digital finance, Fintech enterprises must give utmost importance to research and development and establish partnerships with financial experts and organizations. This study determines that a holistic approach is necessary, which combines emerging technology with a profound understanding of user requirements and concerns regarding privacy, security, and trust. Fintech enterprises have the potential to enhance the security, efficiency, and user-friendliness of the digital financial ecosystem by directly addressing these issues. This, in turn, will augment the popularity and utility of chatbots and Robo-advisors.

This thesis has focused on addressing the significant issue of trust, security, and data privacy (RQ1) by investigating the use and acceptance of chatbots and Robo-advisors (Xia et al., 2023) in the banking sector. The adoption of Robo-advisors is significantly hindered by concerns of trust, security, and data protection despite the sophisticated features and potential efficiency advantages they provide. The study relied on qualitative interviews conducted with Fintech managers and employees, as well as an extensive literature analysis (Jinasena et al., 2023). The research demonstrates that the utilization of Robo-advisors in Fintech services has both advantageous and detrimental effects. While they may offer novel and handy solutions, they can introduce formidable and unsolvable challenges. The primary determinants influencing user trust and acceptability are security, privacy, and trustworthiness. To effectively tackle these issues, it is crucial to carry out regular security audits, adopt upgrades, establish multi-layered security protocols, and employ the latest encryption technologies. The research emphasizes the need for continuous innovation, establishing collaborations with financial institutions, and doing extensive outreach to enhance user confidence and acceptance.

The acceptance of Fintech chatbots and Robo-advisors is heavily influenced by the significance of data privacy, security, and trust (Aw et al., 2024; Roh et al., 2023). Prior scholarly discussions have emphasized the significance of trust in models of technological adoption, therefore reinforcing this perspective. This research contributes to the existing knowledge of the challenges and possible remedies related to the use of Robo-advisors in the financial technology industry. Moreover, it expands the range of the discussion on the acceptance of technology by emphasizing the requirement for continuous technological advancement and the imperative of implementing precautionary measures to address privacy and security concerns. The integration of chatbots and Robo-advisors into financial services needs a comprehensive approach. This method will comprehensively address all aspects, including technological advancement, user enlightenment, rigorous security protocols, and adherence to regulatory requirements. This study suggests that enhancing the perceived expertise of Robo-advisors via continuous research and development and demonstrating their convenience and reliability might significantly enhance consumer acceptability.

The industry's adoption of Fintech chatbots and Robo-advisors is closely linked to how well they address customer concerns over privacy, security, and trust. An all-encompassing approach that emphasizes technological progress, robust security measures, and user-centric communication and design techniques is vital for progress. Building upon prior research inquiries, this section combines interview outcomes and discoveries from the systematic literature review to finalize and analyze Research Question 3. This question aims to comprehend the factors that influence Robo-advisors' users' self-assessment of their proficiency in the Fintech sector. This thesis offers a comprehensive understanding of the intricate process of Robo-advisors adoption by utilizing the TAM, UTAUT2, and the DeLone and McLean (D&M) Model of Information System Success. The research demonstrates that perceived competence is influenced by several factors, including user experience, emotional involvement, contextual support, and functional performance. This thesis examines the utilization and acceptance of chatbots and Robo-advisors in the banking sector to address the crucial inquiry about trust, security, and data privacy (RQ1). The adoption of Robo-advisors is hindered by significant obstacles, including concerns around trust, security, and data protection, despite the sophisticated features and potential productivity benefits they offer. The study was conducted by extensively reviewing relevant literature and conducting qualitative interviews with managers and employees of Fintech companies. The research indicates that the use of Robo-advisors in Fintech services is connected with both good and negative results. While they might provide challenging hurdles, they can also offer innovative solutions. The trustworthiness and desirability of a product are mostly determined by its security, privacy, and reliability. Efficiently resolving these problems requires regular security audits, upgrades, multi-layered security protocols, and cutting-edge encryption technology. To enhance user confidence and acceptance, the research emphasizes the need for continuous innovation, establishing collaborations with financial institutions, and conducting extensive outreach efforts.

The significance of data privacy, security, and trust significantly influences the level of popularity of Fintech chatbots and Robo-advisors. Previous scholarly discussions have reinforced this perspective by emphasizing the significance of trust in the acceptance of technological models. This study contributes to the existing knowledge of the challenges and possible remedies related to Robo-advisors in the financial technology industry. Furthermore, by emphasizing the requirement for continuous technological enhancement and the imperative of implementing measures to tackle privacy and security concerns, it expands the range of topics discussed in relation to the use of technology. A comprehensive approach is required to include chatbots and Robo-advisors in financial services. This strategy will comprehensively address all aspects, ranging from ensuring compliance with legal requirements to providing user education and establishing rigorous security measures. According to this study, enhancing the perceived expertise of Robo-advisors through continual research and development, as well as demonstrating their convenience and reliability, might significantly enhance consumer acceptability.

The widespread adoption of Fintech chatbots and Robo-advisors in the industry will depend on their ability to effectively handle customer concerns around security, privacy, and trust. Adopting a complete approach that emphasizes technological progress, robust security measures, and user-centric ways of communication and design is of utmost importance. In this analysis, Study amalgamates the findings from the interviews with those obtained from the systematic literature review to comprehensively assess and appraise the preceding work. continue the road map of the research study further considering the third part of the research. I conducted a survey to ascertain the factors that contribute to Robo-advisors users' perception of their proficiency in Fintech. This research conducts a comprehensive investigation of the intricate process of Robo-advisors adoption by utilizing the TAM, UTAUT2, and the D&M

Model of Information System Success. Perceived competence is influenced by factors such as user experience, emotional investment, contextual support, and functional performance, as indicated by the research.

8.1 Managerial Implication for Fintech

This thesis offers a substantial amount of valuable information for CEOs and management personnel of financial technology companies, particularly those involved in overseeing the advancement of chatbots and Robo-advisors as components of their services. The acceptance of a user is significantly influenced by trust, security, and data privacy. Therefore, it is crucial to prioritize these concerns. Fintech company leaders should implement a comprehensive range of security measures, regularly update their systems, and do security audits (AlBenJasim et al., 2023). Establishing and maintaining confidence with consumers necessitates adopting the latest encryption technologies and ensuring the confidentiality and integrity of client data. Another crucial aspect is the imperative for continuous innovation and enhanced user experience. Financial technology companies should allocate resources to enhance the functionalities of chatbots and Robo-advisors, aiming to provide customers with more enjoyable and seamless interactions. Enhanced user experiences, resulting from heightened investment in research and development to enhance platform design and usability, can lead to higher acceptance rates.

Fintech CEOs encounter the challenge of reconciling the paradox of hedonic incentives. While Robo-advisors may initially captivate consumers with their novelty and pleasure, in order to sustain long-term engagement, these technologies must seamlessly integrate into individuals' daily routines. These technologies have the capacity to grow more captivating and addictive by means of individualized experiences and ongoing enhancements in service guided by user feedback. The report also highlights that current procedures and social standards may hinder the adoption process. To mitigate the influence of these elements, managers in the Fintech business can implement strategic marketing and education campaigns that emphasize the characteristics, benefits, and user-friendliness of their products. In order to convince doubters and promote wider use, it is imperative to demonstrate the tangible advantages of chatbots and Robo-advisors.

Utilizing models such as TAM, D&M, and UTAUT2 can aid in comprehending the many factors that contribute to the adoption of technology (Schmitz et al., 2022). Fintech businesses should consider these frameworks and prioritize technical aspects, user engagement, enabling conditions, and perceived value while developing and enhancing their products. Emphasizing the user is of utmost importance while determining a development approach. Fintech firms may enhance the user-friendliness of their chatbots and Robo-advisors by acquiring knowledge about the many factors that impact consumers' judgments of proficiency and suitability. By using this approach, we can ensure that these technologies will effectively fulfill their intended function and resonate with the target users. Finally, the improvement of chatbot and Robo-advisor technology may be accomplished by fostering collaboration with financial institutions and systematically gathering client feedback. Through collaboration, Fintech enterprises may effectively adapt to evolving customer demands and technological improvements, hence ensuring the competitiveness of their products. Fintech CEOs and managers may enhance customer experiences, operational economies, and competitiveness in the dynamic Fintech ecosystem by embracing these practical consequences and boosting the acceptance and usability of chatbots and Robo-advisors.

Drawing on the fifteen Hungarian expert interviews, FinTech managers, both in Hungary and across the wider European Single Market, should treat visible trust architecture as their foremost strategic lever: audited cyber-defences, GDPR-compliant privacy dashboards, and the explicit display of domestic-regulator licenses (e.g., MNB in Hungary, BaFin or the CSSF elsewhere in the EU) must precede any marketing of convenience or low fees. Because interviewees stressed localization and inclusivity, firms should pair a mobile-first, fully translated interface with assisted, branch-based onboarding for low-digital literacy cohorts while redoubling investment in user education that frames security features and algorithmic fairness in plain language. Finally, CEOs should pursue co-development alliances with legacy banks to ease API integration and publicly signal joint accountability. This approach satisfies Europe’s tightening supervisory climate and converts institutional heritage into a competitive advantage for robo-advisor roll-outs continent-wide.

8.2 Published and Under Review Work.

Following publication, conference presentation, and under review work is relevant to the research questions mentioned in the thesis.

Table 22 Published and Under review work

Relevant Research Question	Title	Published
Q3	B2B Financial Sector Behavior Concerning Cognitive Chatbots.	Presented at IEEE conference. Published at IEEE Explore

	Personalized Contextual Chatbots in the Financial Sector	
Q2, Q3	Shopping using mobile applications and the role of the technology acceptance model: Purchase intention and social factors.	Published in Hungarian Statistical Review
Q2	Current Trends of Development in Chatbot Systems	Published in Specialusis Ugdymas
Q3	How Can Business Agility be Addressed with Artificial Intelligence?	Presented at OGIK'2022 National Business Informatics Conference. (2022)
Q3	Why should Chatbots be like Humans? Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Belief Desire Intentions (BDI) Model-based investigation	Presented at FIKUSZ 2021 International Conference Obuda University
Q1	Robo-Advisors Challenges and Solutions	Presented at Conference on Digital & Cognitive Corporate Reality and AI Transformation October 25, 2024

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10. Appendix

Survey Items

Constructs	Items	Scale Item	Source
Perceived information quality (PIQ)	PIQ1	The AI Robo-advisors gave me the details I needed.	Trivedi 2019
	PIQ2	The information provided by an AI Robo-advisor concerning my questions or problems is helpful.	
	PIQ3	I am satisfied with the accuracy of the AI Robo-advisors' information	
Perceived system quality (PSYQ)	PSYQ1	I find using AI Robo-advisors makes it easy to become skilled.	Trivedi 2019
	PSYQ2	I think the AI Robo-advisors are user-friendly.	
	PSYQ3	Using an AI Robo-advisor needs minimal mental effort and a very quick reaction.	
Perceived service quality (PSEQ)	PSEQ1	I am pleased with the services the AI Robo-advisors offer.	Trivedi 2019
	PSEQ2	Services offered by the AI Robo-advisors understand my problems and requests.	
	PSEQ3	Services offered by the AI Robo-advisors respond to my queries at an appropriate time.	
Perceived ease of use (PEOU)	PEOU1	The use of AI technology for the implementation of AI Robo-advisors does not take great mental effort	Kasilingam, 2020
	PEOU2	It would be quick for me to learn to run AI Robo-advisors using AI technology	
	PEOU3	It is not difficult to work with an AI Robo-advisor using AI technology; it is easy to understand what is happening.	
Perceived usefulness (PU)	PU1	Based on AI technology, the AI Robo-advisors will be helpful to me.	Kasilingam, 2020
	PU2	Based on AI technology, the AI Robo-advisors will improve my effectiveness.	
	PU3	Based on AI technology, the AI Robo-advisors will improve my productivity.	
Perceived trust (PT)	PT1	I assume that by using the AI Robo-advisors, personal information is to be kept confidential with the adoption of AI technology.	Kasilingam, 2020
	PT2	I am certain that the AI Robo-advisors, constructed with AI technology, provide security measurements.	

	PT3	Privacy is well protected with the adoption of AI technology in the AI Robo-advisors.	
Perceived risk (PR)	PR1	I consider the AI Robo-advisors service risky.	Trivedi 2019
	PR2	I perceived that there was a risk that something could go wrong in the outcome when using the AI Robo-advisors.	
	PR3	I feel the result and the effect of AI Robo-advisors service are hard to predict.	
Customer experience (CE)	CE1	I love to use the AI Robo-advisors.	Trivedi 2019
	CE2	It's interesting to use the AI Robo-advisors.	
	CE3	I am pleased about the experience of using AI Robo-advisors.	
Attitude towards technology (ATT)	ATT1	It is a smart idea to use an AI Robo-advisors built on AI technology for customer service.	Kasilingam, 2020
	ATT2	I like using AI Robo-advisors built on AI technology for customer service.	
	ATT3	Using AI Robo-advisors built on AI technology for customer service would be pleasant.	
Intention to adopt (ITA)	ITA1	Now, I intend to adopt AI Robo-advisors for personalized contextual customer service.	Kasilingam, 2020
	ITA2	I intend to adopt an AI Robo-advisor for personalized, contextual customer service, assuming that I have access to it.	
	ITA3	I intend to inform subject matter experts to adopt AI Robo-advisors for personalized, contextual customer service.	
Performance Expectancy (PE)	PE1	I may find the robo-advisor useful for my investment	(Venkatesh, Thong, & Xu, 2012)
	PE2	Using the robo-advisor enables me to find investment targets more quickly.	
	PE3	Using the robo-advisor increases the performance of my investment.	
	PE4	If I use the robo-advisor, I will increase my profitability.	
Effort Expectancy (EE)	EE1	My interaction with the robo-advisor would be clear and understandable	(Venkatesh, Thong, & Xu, 2012)
	EE2	It would be easy for me to become skillful at using the robo-advisor	
	EE3	I would find the robo-advisor easy to use	
	EE4	Learning to operate the robo-advisor is easy for me.	
Social Influence (SI)	SI1	People who are important to me think that I should use robo-advisor	(Venkatesh, Thong, & Xu, 2012)
	SI2	People who influence my behavior think that I should use robo-advisor	
	SI3	People whose opinions I value prefer that I use Robo-advisor.	
Facilitating Conditions (FC)	FC1	I have the resources and knowledge necessary to use the robo-advisor	(Venkatesh, Thong, & Xu, 2012)
	FC2	The robo-advisor is compatible with other systems I use	
	FC3	A specific person is available for assistance with system difficulties.	
Behavioral Intention (BI)	BI1	I intend to use the system in the next few months	(Venkatesh, Thong, & Xu, 2012)
	BI2	I predict I will use the robo-advisor in the next few months.	
	BI3	I plan to use the robo-advisor in the next few months.	
USE/Attitude	U1	Using the robo-advisor is a good idea	(Venkatesh, Thong, & Xu, 2012)
	U2	The robo-advisor makes investing more interesting.	
	U3	Investing in the system is fun.	
	U4	I like investing with the robo-advisor	
Hedonic motivation (HM)	HM1	Using Robo-advisor would be fun.	(Venkatesh, Thong, & Xu, 2012)
	HM2	Using a robo-advisor would be entertaining.	
	HM3	Using a robo-advisor would be enjoyable.	
Prive Value (PV)	PV1	Robo-advisor is reasonably priced	(Venkatesh, Thong, & Xu, 2012)
	PV2	Robo-advisor is good value for the money.	
	PV3	At the current price, the robo-advisor provides good value.	

Habit (HA)	HA1	The use of robo-advisor has become a habit for me.	(Venkatesh, Thong, & Xu, 2012)
	HA2	I am addicted to using robo-advisor.	
	HA3	I must use a robo-advisor	
	HA4	Using a robo-advisor has become natural to me.	

Semi-Structured Interview Part 1 (Pakistan)

1. Can you describe the role and functionality of Robo-advisors in your organization?

2. What motivated your organization to implement Robo-advisors in your services?

3. How do you believe Robo-advisors have impacted customer trust in your fintech services?

4. Can you share any strategies or measures your organization has implemented to enhance the trustworthiness of your Robo-advisors?

5. What are the key security challenges you faced with the integration of Robo-advisors in financial services?

6. Could you elaborate on the security measures in place for your Robo-advisors to protect against potential threats?

7. How does your organization ensure that Robo-advisors' interactions comply with data privacy regulations?

8. Can you discuss any specific challenges you've encountered in maintaining data privacy through Robo-advisors?

9. How has user feedback shaped the development and improvement of your Robo-advisors?

10. In your opinion, what role does the user experience play in building trust and ensuring security through Robo-advisors?

11. Looking forward, how do you see the role of Robo-advisors evolving in the fintech sector?

12. Are there any emerging technologies or innovations that you think will significantly impact how Robo-advisors contribute to trust, security, and privacy in fintech?

13. From your experience, what do you believe is the most significant impact of Robo-advisors on the fintech industry?

14. Do you have any closing thoughts or additional insights on the future of Robo-advisors in relation to trust, security, and data privacy in fintech?

Semi-Structured Interview Part 2 (Hungary)

1. Can you tell me about your experience with using financial technology services (like online banking, investment apps, or mobile wallets) in Hungary?

2. Are you familiar with robo-advisors? Where did you first hear about them?

3. Have you personally used any robo-advisor service in Hungary or another country? Why or why not?

4. What type of financial services do you usually prefer — digital or human-assisted? Why?

5. In your view, what benefits would a robo-advisor provide over traditional human financial advisors?

6. Do you think robo-advisors can help with better investment decisions? Why?

7. Would you trust robo-advisors for personalized financial advice or just for basic recommendations?

8. How important is speed, 24/7 availability, and cost-saving when considering robo-advisors?

9. What would make a robo-advisor easy or difficult to use for you?

10. Are there any digital features that would make your experience better (e.g., simple language, customer support, tutorials)?

11. Do you feel that the Hungarian population (older or less tech-savvy) might face difficulties in using robo-advisors? Why?

12. What factors influence your trust in financial technology platforms in general?

13. Would you trust a robo-advisor provided by a well-known bank more than an independent FinTech company? Why?

14. How much do brand reputation, certifications, or user reviews matter to you in trusting a robo-advisor?

15. What security risks come to your mind when using financial apps or robo-advisors?

16. Would you be worried about cyber-attacks, hacking, or loss of sensitive data while using robo-advisors?

17. What security features would increase your confidence in using robo-advisors?

(e.g., two-factor authentication, encryption, regular audits)

18. Are you concerned about how your financial data is collected, analyzed, or shared by robo-advisors?

19. Would you feel comfortable if your data is used for personalized financial offers or marketing?

20. How important is data transparency to you in digital financial services?

21. What would you expect from companies regarding privacy policies?

22. What actions from a company would help build your trust in using robo-advisors?

23. Do you prefer human customer support available alongside digital platforms? Why?

24. Would you like to have control over what data is shared with the robo-advisor? How?

25. Would a trial version or free demo influence your willingness to try a robo-advisor?

26. What are the main reasons that would stop you from using a robo-advisor?

27. Do you think people in Hungary are generally ready for such technologies? Why or why not?

28. Do cultural or generational factors affect the acceptance of robo-advisors here?

29. What would make robo-advisors more acceptable and trustworthy for users in Hungary?

30. Do you think regulators or government institutions should play a role in ensuring the safety of such platforms?

31. What advice would you give to companies planning to introduce robo-advisors in Hungary?

32. Are there any cultural or legal differences in the use of robo-advisors in Hungary compared to countries outside of Europe?

33. Is there anything else you would like to add regarding your views on robo-advisors, technology trust, or data privacy in Hungary?

Interviewee profiles Qualitative Hungarian Context (Semi-Structured Interview)

Interview ID	Primary industry background	Current role / job level (self-described)
1	Academia – IT & financial-technology law	Full Professor of Information-Technology Law, University sector
2	Academia / FinTech research	Head, Corvinus FinTech Center; Associate Professor (senior academic leader)
3	Academia + FinTech operations	Research Associate (BME) and former TransferWise operations staff (early-career researcher / practitioner)
4	Telecommunications technology	Product Manager, Nokia Hungary (mid-senior product leader)
5	FinTech consulting & investment	Independent FinTech consultant / portfolio investor (senior advisor level)
6	FinTech market analysis	Senior Market Analyst specialising in Hungarian digital banking trends
7	FinTech product user & commentator	Experienced retail FinTech adopter; blogger / industry commentator (mid-career professional)
8	Cross-border digital banking	Private investor and early adopter of licensed robo-platforms (experienced retail user)
9	Financial-services journalism	FinTech journalist / analyst covering CEE markets (mid-career)
10	Digital-payments strategy	FinTech strategy consultant focusing on mobile wallets (senior consultant)
11	Regulatory & compliance advisory	FinTech compliance officer / data-protection specialist (mid-senior)
12	FinTech ecosystem promotion	Industry "fintech expert" engaged in policy advisory (senior ecosystem advocate)
13	Digital-banking user experience	UX researcher in a Hungarian bank (mid-level specialist)
14	Payments & mobile wallets	Senior product strategist, mobile-payments provider (senior manager)
15	Retail investing & wealth tech	Active retail investor; spokesperson for robo-advisor user community (experienced user representative)