Drivers of Continuance Intention for Robo-Advisors in the Evolving FinTech Landscape

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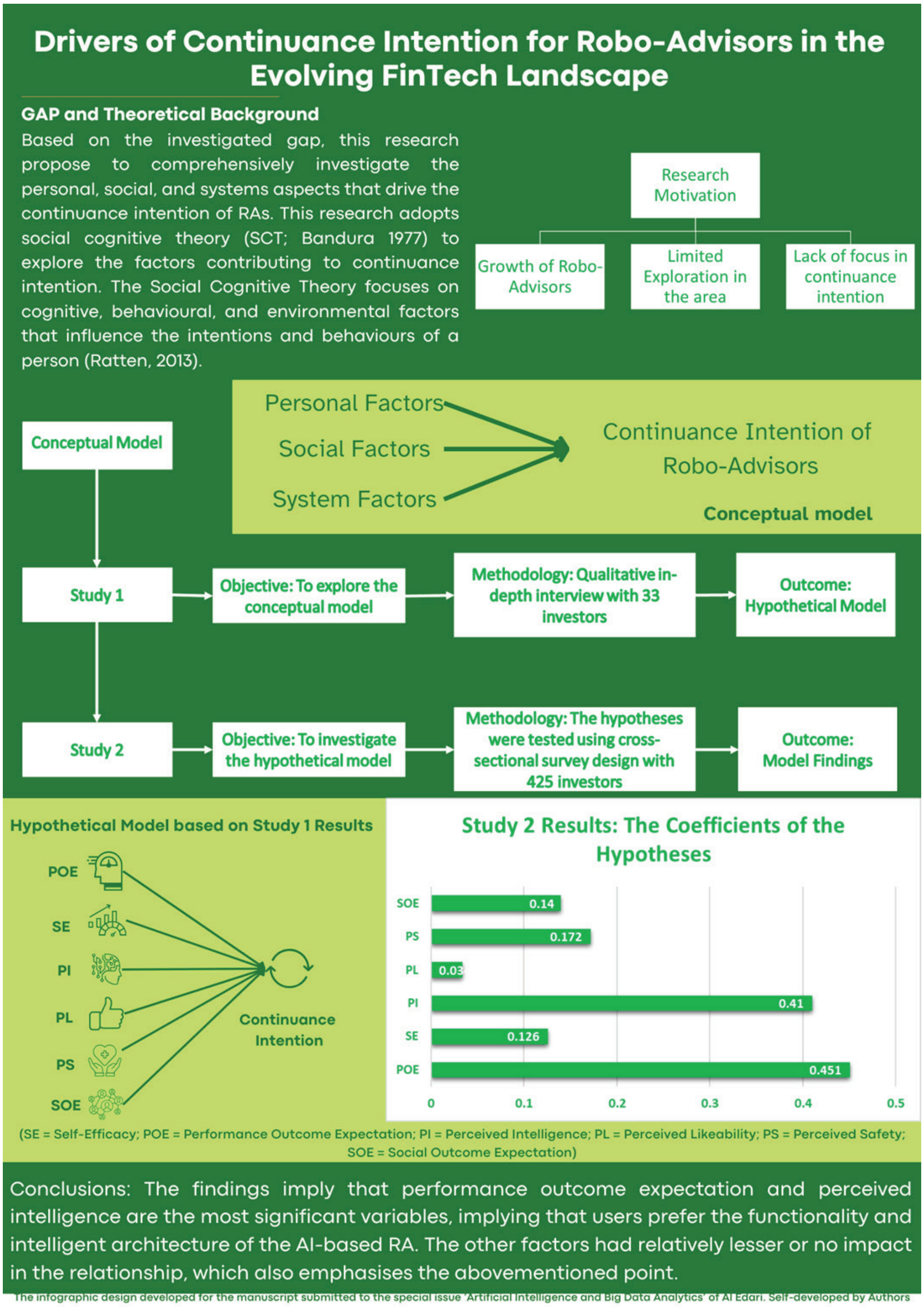
Abstract:

In recent years, the advancement of Artificial Intelligence (AI) and its applications has garnered significant attention, particularly in industries like FinTech, where AI plays a pivotal role. The emergence of Robo-Advisors (RA) within the financial sector has further fueled this growth. However, while the adoption of has been on the rise, there is a scarcity of research focusing on users› long-term continuance intentions with these platforms. To address this gap, this research used an exploratory sequential mixed method research design to explore (Study 1) and identify (Study 2) the factors that drive continuance intention with AI-based RA. The research employed Social Cognitive Theory (SCT) to develop a conceptual model incorporating personal, social, and system factors. Through an analysis involving 425 investors, the study revealed that performance and intelligence emerged as the primary drivers of continuance intention with. By integrating SCT with the existing literature on AI-based financial decisions, the research significantly contributes to the SCT literature. Moreover, the study offers valuable insights for practitioners in the financial industry.

Keywords:

Robo-Advisor; social cognitive theory; artificial intelligence; perceived safety; self-efficacy

Appendix D: An Infographic design of this research.



1. Introduction:

The financial sector has been ready to adopt innovations and plans to spend more on artificial intelligence (AI) than any other industry (Chou et al., 2023). Likewise, investors' knowledge and adoption of Robo-Advisors (RA) is increasing significantly (Zhang et al., 2021). Robo-Advisor is an automated online algorithm that manages and calibrates investors' portfolios (Belanche et al., 2019). RAs are increasingly entering the market and working with clients usually served by highly compensated professional financial advisors or brokers in banks, investing houses, insurance agencies, and wealth management organisations (Bai, 2024). RA, first presented by Wealthfront and Betterment in 2010, provides tailored risk assessments and real-time service modifications through self-service, with little human involvement. Drus (2014) brands RA as the "new wealth management interface of the twenty-first century" and the "next operating system in finance". RA offer investing advice without the need for human participation. In a nutshell, RAs are computerised platforms that assist investors through a fully automated investment advice procedure, from determining financial objectives to monitoring consumer risk profiles and portfolio management (Hasanah et al., 2023). In a competitive fee-based knowledge sector, RAs occupy a financial service niche in FinTech, combining .(financial services with technology, principally information technology (Jiang, 2024

The global RA market is projected to grow at a compound annual growth rate of 25.18%, reaching a market size of $644.6 million (US) by 2029 from $209.7 million in 2024 (Fintech Market, 2024). Despite the potential of FinTech AI apps, research on RA has primarily focused on technological and legal challenges (Figà-Talamanca et al., 2022; Cheng, 2022), neglecting the customer perspective. Limited research on RAsy designs has highlighted the need to enhance the usability of these systems to improve user behaviour (Cheng, 2020). The use of RA in financial decision-making is on the rise (Kasim, 2023). While the growth of RA and its usage has become more relevant in the growing economy, comprehensive feedback to understand the motivating factors demanding high usage of RA is expected to be further investigated.

A Plethora of research has explored the initial adoption and intention to use RAs (Cheng, 2022; Belanche et al., 2019; Flavián et al., 2021; Zhang et al., 2021; Northey et al., 2022; Eren, 2023; Sabir et al., 2023; Wang et al., 2021). On the contrary, little research has investigated end-users' intention to use RA post-adoption (Cheng, 2022). Much of the existing work on RA has focused on explaining antecedents of the adoption of RA, such as perceived usefulness, trust, risk, and emotional factors, in this regard (Cheng, 2020; Xia, 2023; Hohenberger et al., 2019; Chou et al., 2023; Ibrahim, 2023; Bhatia et al., 2021). However, the crucial determinants of continuance usage of RA remain to be discovered. Some studies have examined factors such as task-technology fit, network externalities, gratifications, and flow experience that would help continuance intention (Bhattacherjee, 2001; Cheng, 2020). However, comprehensive models that explain post-adoption behaviour are lacking in RA users (Cheng, 2022; Belanche et al., 2019). The existing literature has mainly focused on the initial stages of the RAs adoption process, but studies that examine the actual long-term use and continuance intention are scarce (Belanche et al., 2019; Gan et al., 2021). There is a need to further validate existing research findings through studies that collect data on the actual usage of RA rather than just present intentions (Belanche et al., 2019). The literature points out a substantial gap in investigating factors driving the continuance intentions of RA, and the industry expectations to drive the continued use of RAs are very high.

Based on the above gap, we propose to comprehensively investigate the personal, social, and systems aspects that drive the continuance intention of RAs. This research adopts social cognitive theory (SCT; Bandura 1977) to explore the factors contributing to continuance intention. The Social Cognitive Theory focuses on cognitive, behavioural, and environmental factors that influence the intentions and behaviours of a person (Ratten, 2013). This gap is relevant for understanding the continuance intention of RA in this complex interplay of technological (system), psychological (personal), and social factors. SCT postulates that beliefs, self-efficacy, and outcome expectations are the major determinants of an individual's behaviour (Ali & Marwat, 2021; Tang et al., 2015). These constructs can explain why users may continue or discontinue using RA after the initial adoption. Compared to other theories like the Technology Acceptance Model (TAM) or the Theory of Planned Behavior (TPB), SCT encompasses all aspects, including cognitive (personal), social, and environmental (technology/system) aspects (Bilali et al., 2021). This theory corresponds very well with the multi-aspect nature of RAsy usage. Many studies have adopted SCT to explain the intention to adopt and continue various technologies, including cloud computing and mobile banking (Ratten, 2013). This evidence affirms the theory to discuss the continuance intention for RA. From the discussion and gap proposed above, this research paper explores the relationship between the SCT factors and the intention to continue RA. This research uses personal, social, and system factors to build the theoretical foundation of SCT in the context of the RA continuing intention. Based on this, the following research questions are proposed.

RQ1: What are the personal, social, and system factors that play a role in the continuance intention of? (Study 1)

RQ2: Which factors (identified in Study 1) are significantly related to the continuance intention of? (Study 2)

This research uses an exploratory sequential mixed method design developed as two studies to investigate the proposed research questions. Study 1 uses a qualitative methodology with an in-depth interview design to explore the conceptual model provided in Figure 1. As a result of the exploration, a hypothetical model is developed. Study 2 empirically investigates the proposed hypothetical model using a single cross-sectional design to analyse the proposed hypothetical model in Figure 3. The discussions and conclusions are consolidated based on the insights from Study 1 and Study 2.

2. Literature and Theoretical Background

2.1. Robo-Advisors in Financial Markets

RA are algorithm-driven digital platforms providing financial planning services with minimal human supervision (Ibrahim, 2023). In recent years, RA has emerged as an intelligent technology platform benefiting the financial services industry (Belanche et al., 2019; Wexler & Oberlander, 2021). These digital platforms use algorithms and automation to provide cost-effective and accessible investment solutions to a broad spectrum of investors (Belanche et al., 2019). RA provide affordable wealth management services for diversified portfolios, investment patterns, and account maintenance optimisations (Belanche et al., 2019). These services become an affordable platform for every section of people in the financial markets (Belanche et al., 2019). RAs algorithmic intelligence enables them to provide customised investment strategies based on the features of the proposed individual risk profiles and financial goals (Xia, 2023). RA is also known for its transparency and ease in providing accurate solutions (Xia, 2023). A rising number of investors have started believing RAs as an effective tool to optimise their wealth management services, influenced by the RA's efficiency and scalability (Ibrahim, 2023).

RAs were initially developed to simplify investment administration in an automated way, and their applications and scope of usage have expanded across various financial services (Todd & Seay, 2020; Hohenberger et al., 2019). RAs can provide complete financial planning services, including career financial goal-setting, retirement planning, tax and risk optimisation, and portfolio design (Ibrahim, 2023; Gazis & Kourmpetis, 2023). Their algorithm-driven interface enables customised recommendations based on each investor's financial goals and interests (An, 2023; Lisauskiene & Darškuvienė, 2021). RAs have become integral partners of various financial services institutions by supporting their financial services and instruments (Waliszewski & Zięba-Szklarska, 2020; Tan, 2020). This integration has broadened these institutes' scope and improved their value and offerings (Boreiko & Massarotti, 2020; Hodge et al., 2020). The scope of RAs is expected to grow as customer portfolios and technological advancements improve, thus changing people's approach towards financial services (Belanche et al., 2019; Bai, 2024). Significant progress has been made by RAs in the field of institutional investor wealth management, including asset management services, pension funds, and endowments, among the organisations that are increasingly using robo-advising platforms (Bhatia et al., 2021; Anshari et al., 2022). By expanding the portfolio of services in the RAs, financial service institutions could internally plan and streamline their investing operations with better efficiency (Hildebrand & Bergner, 2020; Liu et al., 2022). RAs use cutting-edge algorithms and data analytics to provide better outcomes for institutional clients with specialised reporting capabilities, risk management solutions, and sophisticated portfolio-building tools (Bonelli, 2024). Besides retail consumers, RAs are also available for institutional investors (Puhle, 2019; Eren, 2023). These platforms give institutional investors access to various investing techniques and asset options by assisting them to choose better returns (Gan et al., 2021; Sabir et al., 2023). The use of RAs in institutional wealth management is expected to increase, changing the institutional investing landscape as regulatory frameworks adapt to digital innovation in the financial sector (Chou et al., 2023; Zhang et al., 2021).

RA has experienced significant growth in recent years (Hildebrand & Bergner, 2020; Albrecht et al., 2022). This growth is attributed to the rising demand for automated investment solutions (Hasanah et al., 2023; Anshari et al., 2022). According to a report by Statista, global assets under management (AUM) by RA exceeded $1.2 trillion in 2023, with projections indicating a rise to over $4.3 trillion by 2028 (Zhang et al., 2021). A survey by Deloitte revealed that nearly 70% of millennials are open to utilising RA for their investment needs, underscoring the significant potential for further expansion in the retail investor market (Junhui, 2023). With this robust growth and increasing acceptance among investors, RA is poised to play an even more significant role in the financial services industry in the coming years (Puhle, 2019; Gazis & Kourmpetis, 2023).

2.2. Theoretical background

Bandura proposed the Social Cognitive Theory (SCT), which emphasises reciprocal interaction between cognitive processes, behaviour, and the environment in shaping human learning and development (Bandura, 1977; Harinie, 2017). The theory posits that individuals also indirectly learn by observing others and the consequences of their actions (Salanova et al., 2011). The SCT is a branch of self-efficacy, which refers to an individual's belief in their ability to successfully perform a particular behaviour or task (Nelson, 2021). SCT argues that self-efficacy allows individuals to analyse their level of effort and perseverance to achieve a goal (Rodríguez-Sánchez et al., 2011). Moreover, SCT highlights the significance of observational learning, in which individuals adapt social abilities and behaviour (Iroegbu, 2015). In developing observational learning, individuals tend to adapt to social norms, values, and beliefs (Zakeri et al., 2015). This theory has been extensively utilised in various disciplines, such as psychology, education, communication, and organisational behaviour (Corcoran, 1991).

Using SCT in technology-related research has opened new avenues for enhancing learning, behaviour modification, and user engagement (Phan, 2013). Previous research has applied SCT frameworks in technology-related studies to gather more knowledge in the areas of observational learning (LaForge-MacKenzie & Sullivan, 2014), technology-based self-efficacy (Stanley et al., 2020), and human response to technology-related environments (Ilmiani et al., 2021). SCT has been used across various diverse technology-related domains such as education and e-learning (Mazziotta et al., 2011), healthcare (Tan et al., 2021), social media and online communities (Donkoh, 2023), and workplace training and development (Delport, 2019). Thus, SCT provides a valuable framework for developing and enhancing technology applications across various domains. Integrating SCT with RA can help developers understand the expected functionalities of users, thus enhancing their design and functionality.

Technology advancements can enhance user engagement and facilitate improved financial decision-making Shiau & Luo (2013). SCT encompasses various context-dependent dimensions, focusing on personal and environmental factors when integrating with technology (Roberts & Griffith, 2019). Personal factors such as subjective knowledge, cognition, and outcome expectations are pivotal in technology contexts, while environmental factors include social aspects and the overall technological setting (Ma, 2023). Social factors like social expectations, social influence, and social self-efficacy significantly influence positive intentions towards technology (Wang et al., 2021). System factors delineating RA's inherent characteristics are crucial for understanding user behaviour (Ismail, 2022).

Research on RA is expanding, with studies exploring trust and user willingness to adopt these platforms (Shin et al., 2022). Nevertheless, a research gap exists concerning the impact of personal, social, and system factors on developing continuance intention for using RA. Expectation-Confirmation Theory underscores the significance of comprehending user expectations and performance to ascertain the long-term effects of technology (Juliana et al., 2021). Subsequently, future research endeavours aim to investigate the influence of personal, social, and system factors on RA and their impact on continuance usage intention (Ong et al., 2022). Based on the series of discussions above, this research proposes to investigate the impact of personal, social, and system factors underlying RA and its impact on the continuance usage intention of RA (Figure 1). The conceptual model is a basic idea used to generate the hypothetical model using a qualitative study (Study 1). Later, the hypothetical model is tested empirically to understand the results (Study 2).

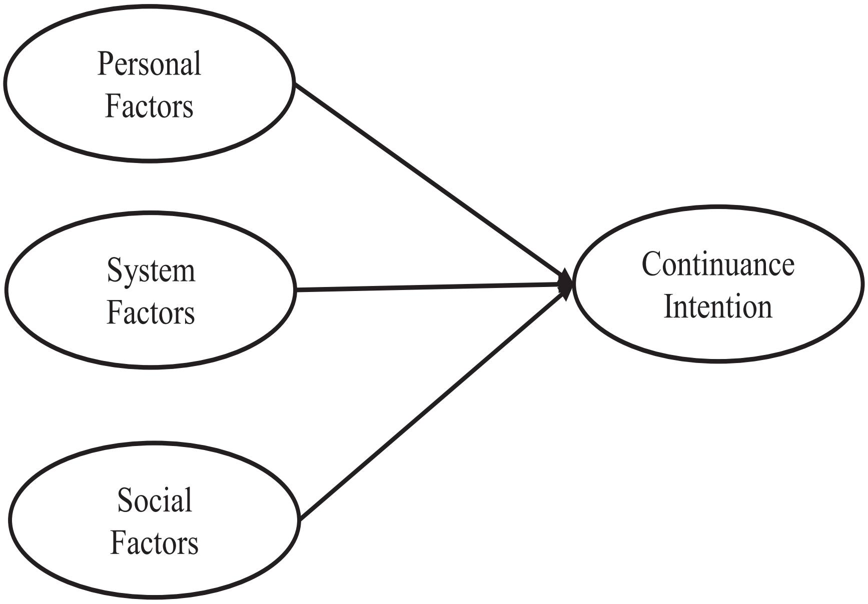


Figure 1: Conceptual model of this research

3. Study 1

3.1. Study Design

This study follows a qualitative design in which 33 investors who use RA regularly are interviewed. Based on the interview and the results of the qualitative analysis, the conceptual model is expanded. Initially, the participants were given a brief presentation about the characteristics of the RA. Despite having a better idea about the RA, the participants showed good interest in developing the knowledge. Following the presentation, the RA shared their experience and participated in a semi-structured, in-depth interview process. The interview was oriented based on the conceptual model given in Figure 1. The questionnaire consisted of both open-ended and close-ended questions. On average, the interview lasted 16 minutes with the participants (maximum = 38 minutes; minimum = 9 minutes). All 33 investors who participated in the interview answered all the questions. The interviews were conducted through physical interviews and online interviews. The indicative questions of the interview are provided in Appendix A.

The investors who participated in Study 1 had at least once used the RA and had experience using it to a maximum of 12 times (mean = 6.92; Std. Dev = 2.05). Fifteen of those who participated in the interview were female, and Eighteen were male. The investors were selected based on a non-probabilistic sampling method in which the authors chose the participants in a judgemental way. The participants are identified through various online and offline sources representative of the targeted sample. A self-developed questionnaire vetted by six experts from academics and industry. The refined semi-structured questionnaire was used to interact during the interview process. The participants' profile is presented in Appendix B

3.2. Data Analysis

The responses of the participants are converted to verbatim data. The verbatim data were evaluated using a five-step approach (Braun and Clarke, 2022; Dwivedi et al., 2023; McCrudden and McTigue, 2019). Firstly, a thorough reading of the recorded interview transcripts was done to ensure that the data and discussion represented the proposed conceptual model. The interview transcripts were created in the second stage as closed phrases to fit the study's conceptualisation. For instance: "I expect performance from the RA with matching my outcome" (P12), "Since I provide my data into the RAs, I expect safe features that the data should not be misused" (P13), and "I always value the use of RA based on their intelligence in providing valuable responses" (P16). The final phase involved creating an axial coding system by methodically combining open codes that were created from the phrases. Examples of codes assigned to the above statements are "Performance Expectation" for P12, "Safety" for P13, and "Intelligence" for P16. The fourth stage involved further grouping the axial coding labels into categories based on theme congruence, in accordance with the principles of selective coding. For instance, "Perceived Safety" is where the codes "safety", "trust", "privacy", and "threat" are grouped. In the fifth and final stage, an extended hypothetical model is created by fitting the resulting labels and codes into the conceptual model shown in Figure 2. NVIVO and GEPHI 0.10 were utilised to interpret the codes and visualise the pattern of relationships.

3.3. Results of Study 1

The study 1 qualitative analysis explored the users' perception within the representation of the conceptual model presented in Figure 2. Based on the analysis of the transcripts generated from the interview with 33 RA users, the conceptual model is further expanded to identify six main exogenous variables that build user's intentions to continue with RA, namely, self-efficacy, performance outcome expectation, social outcome expectation, perceived intelligence, perceived likeability, and perceived safety.

3.3.1. Self-Efficacy

Self-efficacy is identified as one of the personal factors. The analysis of the transcripts revealed various labels related to Self-Efficacy, such as self-confidence, self-belief, efficacy, self-competence, and assurance. Based on identified labels, the construct Self-Efficacy is identified as a major personal expectation from the users. Self-efficacy refers to the confidence and beliefs users instil in them to use the technology efficiently (Balakrishnan et al., 2022); the case also applies to RAs. During the interaction, users felt they had more confidence in using the RA and the usable system developed for users' convenience, which motivated them to continue using it.

P2 stated, "The more confident I feel about using this tool, the more I will be happy to use it in the future as well."

P22 stated, "I believe I can use the RA, which motivates me to subscribe to these tools continuously."

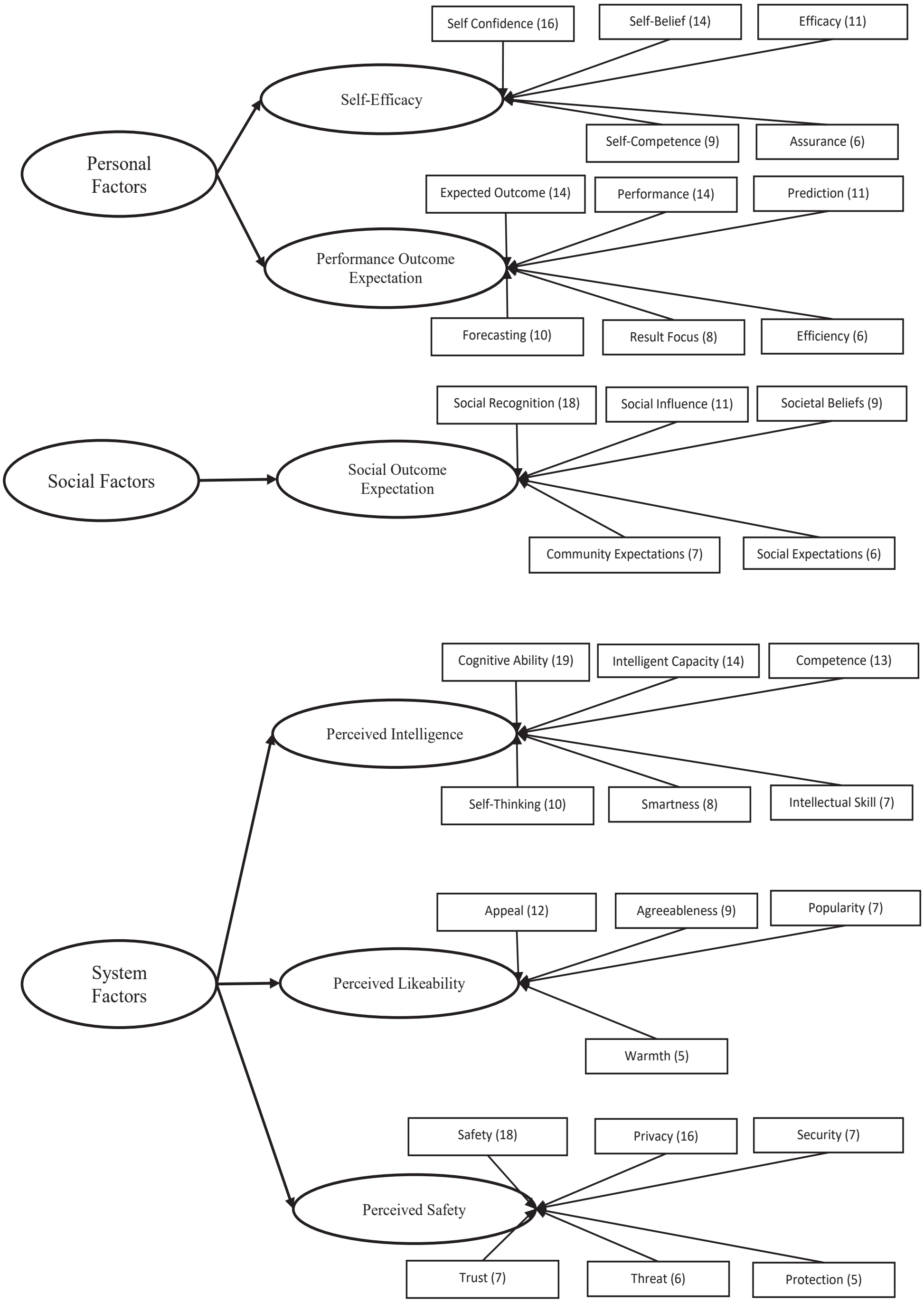


Figure 2: The coding figure of Study 1 (n=33)

3.3.2. Performance Outcome Expectation

Performance Outcome Expectation is identified as the next factor in the personal factors. The transcripts' analysis revealed various labels related to Performance Outcome Expectations, such as outcome expectation, performance, efficiency, predictive and forecasting capability, and result focus. Based on the meanings of the labels, the study identified and named "Performance Outcome Expectation" as a variable. Performance outcome expectations for RAs involve users' beliefs about the results they will achieve using these AI-driven systems (Roongruangsee & Patterson, 2024). During the interaction, users felt they had more confidence in using the RA and the usable system developed for users' convenience, which motivated them to continue using it.

P19 stated, "The RA should have an enhanced ability to perform well and respond well, which will help me to decide about using it in the future as well."

3.3.3. Social Outcome Expectation

Social Outcome Expectation refers to the expected results or consequences of a social interaction accustomed to a specific context (Pfattheicher et al., 2022). Every event has a social outcome, and so does technology. Sometimes, it may be favourable or otherwise unfavourable so that the outcome can be measured. Every individual, especially those who are socially oriented, expects a favourable social outcome for every action. The following labels were identified when analysing the verbatims: social recognition, social influence, societal beliefs, community expectations, and social expectations. Based on the combined meaning of the identified labels, social outcome expectation was named as a holistic construct. Social outcome expectation involves predicting and articulating the intended impacts of social interactions or interventions. Individuals may expect their interactions with the RA to be socially recognisable, leading to long-term use of the technology.

P4 stated, "I feel there should be social recognition while using RAs, as it helps me to use it confidently even in the future."

P17 stated, "I expect social support from my peers and groups while using the RAs."

3.3.4. Perceived Intelligence

Perceived intelligence refers to the cognitive process based on which a RA operates (Zhang et al., 2021). In most cases, it is measured based on the accuracy, clarity, optimised suggestions, and contextual replies provided by the RA. This study's construct is derived from the labels identified during the conversation: cognitive ability, intelligence capability, competence, self-thinking, smartness, and intellectual skill. The identified labels commonly explain the intelligent factor present in the RAs. The interview transcripts exhibited that these labels are mainly connected with the role of continuance intention among the users. Thus, based on the qualitative interview, it is evident that intelligence is an important factor investors expect from RA, which can yield long-term engagement and benefits. An example of the transcripts that explain the labels is given below.

P8 stated, "I am amused by the cognitive and AI architecture that the RA is made of; I will continue using it."

P33 stated, "AI-based intelligence is more effective than traditional suggestions, which will allow me to use it in the future."

3.3.5. Perceived Likeability

Likeability is the subjective belief that people have concerning a person, product, or service, formed from several attributes and interactions (Blut et al., 2021). The likeability of RA is the subjective perception of users concerning their investment experiences and interactions with digital platforms that operate autonomously. It includes the functionality of the RAs, the level of service and responsiveness of the customer service, transparency regarding the fee structure and the strategy used to invest, and the personalisation of investment advice. Based on the transcripts, it can be understood that appeal, agreeableness, popularity, and warmth shape likeability toward RA. The discussion with the participants shows that likeability with the RA can improve the intention of a long-term association with the RAs. An example of the transcripts that explain the labels is given below.

P1 stated, "The appeal of RA motivates me to use it again."

P24 stated, "The warmth that the RAs exhibit is good, and I like to have future associations with it."

3.3.6. Perceived Safety

Perceived safety explains a user's perceived secureness and protection when associated with technology (Widyanto et al., 2022). Previous research has identified perceived safety as an important tool to build trust and long-term association with a technology (Bartneck et al., 2009). In the case of RA, perceived safety explains the sense of safety that the tool exhibits in compliance with financial regulations and with the effort to preserve user trust and security. The interviews show that perceived safety is shaped by the following labels: safety, privacy, security, trust, threat, and protection. The interview participants exhibited that they continue with the services when their data is protected. So, based on the discussion with the participants, it is explained that the secured system of RA can lead to a long-term association with its users. An example of the transcripts that explain the labels is given below.

P5 stated, "I believe the RA provides secured access. If the security can be sustained, I do not mind using the portal again."

P27 stated, "Security is crucial in financial decisions if RA can provide it. Iam happy to continue using the services."

Based on the labels and primary constructs discovered from the transcripts, this study proposes the theoretical model in Figure 3.

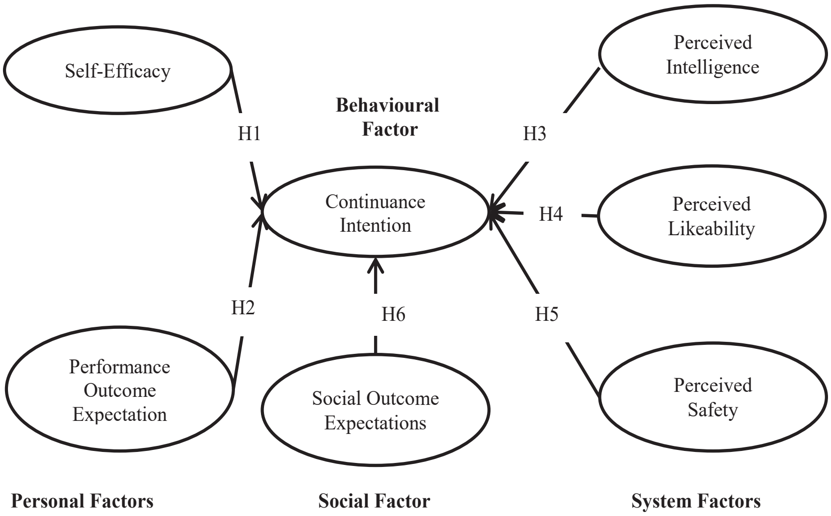


Figure 3: Hypothetical model of this research

4. Hypothesis development

4.1. Personal factors to continuance intention

Bandura (1977) describes self-efficacy as an individual's judgment of their ability to perform actions required to achieve intended outcomes. Previous research has supported that self-efficacy can support improve financial decision-making and the same can have high control over operating financial tools (Farrell et al., 2016; Riaz et al., 2022; Ali & Marwat, 2021; White, 2021; Purwidianti et al., 2022). Purwidianti et al. (2022) explain that financial self-efficacy helps manage financial goals and optimise outcomes effectively. Moreover, other studies have supported that self-efficacy can improve the financial freedom to make decisions and operate tools that benefit with better experience (Riaz et al., 2022; Godase, 2023; White, 2021). Kwak et al. (2022) supported that users who adopt AI-based financial decisions tend to have stronger continuance intention tendencies. Furthermore, literature has supported integrating self-efficacy theories with AI technology to have positive intentions (Kwak et al., 2022). Based on the above discussion, this study posits that self-efficacy can positively influence continuance intention.

H1: Self-efficacy significantly positively influences the continuance intention to use.

Performance outcome expectations are the benefits or outcomes users think they could get from AI-based technology, like efficiency, effectiveness, and overall performance enhancement. Previous research has supported the idea that expected performance from technology can shape users' continuance intentions (Yusvianto, 2024). In this sense, users with higher expectations about the positive outcomes they can achieve with AI-based technologies are likelier to continue using it because of the perceived performance improvement (Sorathiya, 2024). In addition, the association between users' performance outcome expectations and the outcomes observed while using AI-based RA are related to continued interaction and satisfaction (Kim et al., 2023). More research emphasises that user satisfaction can strongly influence their continued use of technology services, and satisfaction is closely linked to the expectations of how a product will perform (Kim et al., 2023; Na et al., 2023). Thus, a better product or technology performance is more likely to demonstrate loyalty to the platform, which otherwise motivates continuous use (Kim et al., 2023). Based on the above discussion, this study posits that performance outcome expectations will significantly influence the continuance of the use of RA.

H2: Performance Outcome expectations significantly positively influence the continuance intention to use.

4.2. System factors to continuance intention

Perceived intelligence refers to users' beliefs about AI systems' cognitive capabilities and smartness (Pillai & Sivathanu, 2020), which results in various outcomes. Previous research has highlighted the role of AI intelligence in shaping users' intentions and attitudes (Pillai & Sivathanu, 2020; Tang et al., 2022; Balakrishnan & Dwivedi, 2021). Also, research has supported that intelligence can play a crucial role in developing adoption intention in chatbots and banking services (Pillai & Sivathanu, 2020; Tang et al., 2022). Speaking of a broader concept, Chuah et al. (2021) shed light on how factors about human likeness (anthropomorphism and perceived intelligence) play a significant role in service robot adoption. Users who perceive AI systems as intelligent are more likely to engage with these technologies, leading to enhanced user experiences and continued usage (Balakrishnan & Dwivedi, 2021). In financial decision-making, RA exhibits greater intelligence to provide optimal results to the users. Thus, perceived intelligence can contribute to users' intention to continue using it. Based on the above discussion, the below hypothesis is proposed.

H3: Perceived intelligence significantly positively influences the continuance intention to use.

Perceived likeability refers to users' subjective perceptions concerning AI systems' attractiveness, friendliness, and appeal (Geys, 2014). Previous research has supported the likeability of AI tools to enhance attitudes and behavioural intentions associated with AI (Geys, 2014; Dabas et al., 2022). Research has also shown that perceived likeability associated with AI-based systems can influence user satisfaction and intention to continue (Yeh et al., 2022). Seth (2024) supports that the emotional connection developed due to the likeability factor can motivate users to adopt AI services again. Similarly, AI likeability can enhance the experience, resulting in a better outcome (Seth, 2024). Research has previously integrated the theoretical background of continuance intention with AI likeability (Yeh et al., 2022). Given that financial decision-making and its recommendation can be realistic and that the likeability factor with the AI tool is possible, the study posits the following hypothesis based on the above discussion.

H4: Perceived likeability significantly positively influences the continuance intention to use.

Robotics and AI literature has consistently stressed perceived safety as an important parameter in any study that captures human-robot interaction. Perceived safety refers to the user's belief that the system is threat-free (Schreibelmayr, 2023). Users develop their safety perception in AI based on various underlying factors, such as the accuracy of the information provided, data security, and critical protection (Schreibelmayr, 2023; Mahdavi, 2024). Based on the favourable safety perceptions, users build their intention to adopt or continue with AI-based services. Antwi (2024) supports the idea that safety builds users' continuance intentions. Previous research has highlighted that AI-based algorithms can detect irregularities that may be present in the AI system, if any and can provide a more secure network for financial transactions (Schreibelmayr, 2023; Mahdavi, 2024; Antwi, 2024). Mahdavi (2024) suggests that providing a more secure and safe AI system is required to develop trust and long-term association with the AI system. Based on the above discussion, the study posits that perceived safety can significantly influence the continuance intention of RA.

H5: Perceived safety significantly positively influence the continuance intention to use.

4.3. Social factors to continuance intention

Social outcome expectation refers to customers' reliance on third-party recognition while considering an application's adoption and subsequent use. Milani (2019) studied the adoption of RA in Italy by applying the above model and found that social influence positively affected the adoption of RA. For a similar study performed in the Malaysian context, social influence was proved to have a positive and statistically significant effect on the intention to adopt RA. Similar results were observed even for electronic wallets (Lim et al., 2024) and fintech/digital finance solutions (Gerlach et al., 2019). Khadka (2023) suggests that AI systems should align with social needs rather than only focusing on personal needs, which can generate positive user responses. Moreover, by integrating such social factors into the AI system, users will receive better reception, leading to continued use. In the case of RA, the users may expect a social performance and recognition to showcase their performance to third-party people. Based on the above discussion, the study posits that social outcome expectation can positively lead to the continuance usage of RA.

H6: Social outcome expectation significantly positively influences the continuance intention to use.

5. Methodology

5.1. Design and Procedure

Study 2 followed a single cross-sectional design survey design. One thousand eight hundred financial investors were contacted personally, of which 445 were found to be using RA for their financial planning, and they agreed to participate in the study. A survey was conducted during the first quarter of 2024 with 445 Indian investors, of which 425 usable data was derived. The 425 investors, on average, have transacted or used RAs multiple times (average times = 7.12 times; Max = 18; Min = 1). The survey was conducted online through LinkedIn, Twitter, email, and other sources, and a link to the questionnaire form was shared with the respondents. The data was collected within a time frame of 20 days. Given the 28 parameters for the seven constructs, 425 is sufficient to test the proposed model, considering ten samples for each parameter (Boomsma, 1987). Table 1 shows the socio-demographic information about the participants. As seen from the table, the sample is well diversified across the financial investors with adequate knowledge about the RAs, thus supporting the sample representativeness aligned with the study objectives.

5.2. Questionnaire and Measures

The questionnaire consisted of seven constructs on an interval scale and eight socio-demographic variables measured on nominal and ordinal scales. The items for self-efficacy, performance outcome expectation, social outcome expectation, perceived intelligence, perceived likeability, perceived safety, and continuance intention are derived from previous research (Lin & Huang, 2008; Niederhauser & Perkmen, 2010; Bartneck et al., 2009; Balakrishnan et al., 2022; Balakrishnan & Dwivedi, 2021). Self-efficacy is derived from Lin and Huang (2008), performance outcome expectation and social outcome expectation are derived from Niederhauser and Perkmen (2010), perceived intelligence, perceived likeability, and perceived safety are derived from Bartneck et al. (2009), and Balakrishnan et al. (2022), and continuance intention is derived from Balakrishnan and Dwivedi (2021). All the items of the constructs are measured on a seven-point Likert scale ranging from Very Strongly Agree (7) to Very Strongly Disagree (1). The complete scale information is provided in Appendix C.

Table 1: Social demographic information about the study participants			
Socio-demographic		Frequency	Percentage
Variables	Characteristics	N = 425	(%)
Gender	Female	203	47.76%
	Male	222	52.24%
Age	Under 30 years	165	38.82%
	to 40 years 31	148	34.82%
	to 50 years 41	79	18.59%
	Above 50 years	33	7.76%
Previous Experience with RA for Financial Planning and Trading Activities	to 5 times 1	146	34.35%
	to 9 times 6	161	37.88%
	to 14 times 10	106	24.94%
	to 18 times 15	8	1.88%
Objective to use RA	Investment Planning	81	19.06%
	Mortgage and Loan	73	17.18%
	Stock Trading	233	54.82%
	Other services	38	8.94%
Source of knowledge about RA	Friends	38	8.94%
	Attended Lectures	68	16.00%
	Official Colleagues	186	43.76%
	Social media and Internet	133	31.29%

5.3. Analysis

Study 2 model was tested using a two-step Structural Equation Modeling (SEM) technique. Initially, Confirmatory Factor Analysis (CFA) was conducted to assess the measurement model's reliability, content validity, convergent validity, and discriminant validity. This step ensured that the items used in this study explained the constructs' intended latent meaning and the difference in measurement. We performed the Common Method Bias Analysis (CMB) to ensure that measurement error does not affect our data and analysis. Following this step, we utilised SEM to verify the theoretical propositions in Figure 3. Prior investigations already backed SEM usage in testing hypothesis models (Fornell and Larcker, 1981; MacCallum and Austin, 2000; Gefen et al., 2000) to explore relationships among variables in the theoretical framework. We employed SPSS Statistics 24 and SmartPLS 4.0 for all statistical analyses. The research hypotheses were successfully tested by employing advanced statistical methods such as Confirmatory Factor Analysis (CFA), Covariance matrix-based Structural Equation Modelling (CMB), and Structural Equation Model analysis. As a result, this analytical strategy guarantees accuracy and consistency in the results obtained.

Table 2: Confirmatory Factor Analysis results

Constructs	Measures	Mean	Std. Dev	Standardised factor loadings	Cronbach Alpha	Average Variance Extracted (AVE)
Continuance Intention	CI1	4.449	1.740	***0.959	0.970	0.888
	CI2	4.551	1.801	***0.939		
	CI3	4.508	1.871	***0.944		
	CI4	4.398	1.693	***0.929		
Perceived Intelligence	PI1	4.798	2.019	***0.969	0.982	0.914
	PI2	4.732	1.952	***0.944		
	PI3	4.638	1.912	***0.968		
	PI4	4.619	1.894	***0.944		
	PI5	4.607	1.843	0.954		
Perceived Likeability	PL1	4.755	2.010	***0.964	0.979	0.903
	PL2	4.732	1.876	***0.947		
	PL3	4.602	1.890	***0.961		
	PL4	4.626	1.816	***0.934		
	PL5	4.565	1.809	0.944		
Performance Outcome Expectation	POE1	4.365	1.771	***0.959	0.965	0.904
	POE2	4.506	1.717	***0.922		
	POE3	4.464	1.798	***0.959		
Perceived Safety	PS1	4.353	1.829	***0.960	0.963	0.897
	PS2	4.386	1.796	***0.927		
	PS3	4.475	1.828	***0.964		
Self-Efficacy	SE1	3.878	2.007	***0.954	0.966	0.850
	SE2	3.661	1.873	***0.830		
	SE3	4.002	2.053	***0.967		
	SE4	3.744	1.862	***0.914		
	SE5	3.854	1.934	***0.938		
Social Outcome Expectation	SPO1	4.160	1.816	***0.926	0.940	0.839
	SPO2	4.207	1.823	***0.910		
	SPO3	4.186	1.781	***0.912		

Note 1: CFA Fit indices: $\varkappa 2/df = 2.837$; GFI = 0.924 (Good fit>0.9), CFI = 0.968 (Good fit>0.9); TLI = 0.952 (Good fit>0.9); RMSEA=0.066 (Good fit <0.08); Note 2: ***denotes $p<0.001$

Note 3: All the scale items are measured in a five-point Likert scale format, with 5 representing Strongly Agree and 1 representing Strongly Disagree.

5.4. Results

5.4.1. Measurement Model

The measurement model was tested to confirm the three validity requirements (construct, convergent, and discriminant validity requirements). As shown in Table 2, Cronbach's Alpha values exceeded the recommended threshold of 0.70 (Portney and Watkins, 2000). The reliability scores support the consistency of the constructs in the measurement model. Moreover, the standardised estimates (factor loadings) of all items for each construct were above 0.80, and the observed factor loadings confirm the construct's validity requirements. The construct validity also indicates that the items of each construct indicate an inter-construct measurability conformance. Table 3 presents the Average Variance Extracted (AVE), Composite Reliability (CR), and inter-correlation values among constructs, with the square root of AVE values shown on the diagonal. AVE values exceeding 0.50 demonstrate satisfactory convergent validity (Bagozzi et al., 1991). The square root of AVE values shown in the diagonal in Table 3 can be higher than the inter-correlation values between constructs, ensuring discriminant validity per Fornell and Larcker (1981). This result confirms that each construct has discriminatory power, which can express variance among the constructs. The fit indices of the measurement model, presented in Table 2, indicate a good fit of the model to the data. CMB analysis (Podsakoff et al., 2003) is checked to determine whether the data was free of internal bias.

Table 3: Inter-construct correlations and AVE value

	1	2	3	4	5	6	7
Continuance Intention .1	**0.943**						
Perceived Intelligence .2	0.787	**0.956**					
Perceived Likeability .3	0.585	0.657	**0.950**				
Perceived Safety .4	0.749	0.738	0.573	**0.951**			
Performance Outcome .5 Expectation	0.792	0.725	0.551	0.779	**0.947**		
Self-Efficacy .6	0.608	0.620	0.473	0.587	0.549	**0.922**	
Social Performance .7 Outcome	0.748	0.760	0.628	0.730	0.739	0.614	**0.916**

Notes: 1. AVE represents Average Variance Extracted; 2. CR represents composite reliability; 3. Square root of AVEs are presented in the diagonal for each construct in bold format; 4. All values in the correlation matrix are significant at a 99% confidence level

5.4.2. Structural Equation Modelling

The results of the hypotheses are provided in Figure 4. The SEM analysis tested the relationships between the exogenous variables (Self-Efficacy, Performance Outcome Expectation, Perceived Intelligence, Perceived Likeability, Perceived Safety, and Social Outcome Expectation) and endogenous variables (Continuance intention to use RA). Hypothesis 1 indicated a statistically significant but weak positive relationship between Self-Efficacy and Continuance Intention of RA (β = 0.126; SE = 0.031; t = 2.602; p<0.010). Hypothesis 2 showed a statistically significant and strong positive relationship between Performance Outcome Expectation and Continuance Intention of RA (β = 0.451; SE = 0.045; t = 7.220; p<0.000). Hypothesis 3 reveals a statistically significant and strong positive relationship between Perceived Intelligence of RA and Continuance Intention (β = 0.410; SE = 0.041; t = 6.158; p<0.000). The results of Hypothesis 4 showed that Perceived Likeability is not significantly related to Continuance Intention of RA (β = 0.034; SE = 0.031; t = 0.687; p<0.492). Hypothesis 5 indicates a statistically significant but weak positive relationship between Perceived Safety and Continuance Intention of RA (β = 0.172; SE = 0.045; t = 2.667; p<0.008). Users who feel that RA are safe to use are slightly more inclined to continue using them. The results of Hypothesis 6 showed that Social Outcome Expectation is significantly but weakly related to Continuance Intention of RA (β = 0.140; SE = 0.051; t = 2.458; p<0.014). The fit indices of SEM showed a good fit for the overall model ($\chi 2$/df = 2.425; GFI = 0.912 (Good fit>0.9), CFI = 0.957 (Good fit>0.9); TLI = 0.951 (Good fit>0.9); RMSEA=0.066 (Good fit <0.08)).

0.140**

6. Discussion

This research employed an exploratory sequential mixed method design to investigate the conceptual model proposed in Figure 1. Based on the outcome of a qualitative study (Study 1), a hypothetical model is developed in Figure 3. Further, a cross-sectional study is employed (Study 2) to test the model. It was found that, except for hypothesis 4, the remaining hypotheses were supported. A detailed discussion of the results is presented in the subsequent sections.

The results of hypothesis 1 suggested a weak positive relationship between self-efficacy and continuance intention, indicating that individuals with higher levels of self-efficacy are slightly more inclined to continue using RA (Phan, 2013). Self-efficacy, a concept rooted in Bandura's SCT, emphasises that an individual's behaviour is heavily influenced by self-belief (Shahzad et al., 2024). In the context of RA, individuals who perceive themselves as capable of effectively using these platforms may feel more confident in managing their investments, thereby impacting their intention to continue using such services. Furthermore, hypothesis 2 identified a strong positive relationship between performance outcome expectation and continuance intention, highlighting that individuals expecting high-performance outcomes from RA are likelier to persist in using these services (Cheng, 2020). Performance outcome expectation, which reflects users' beliefs about technology like RAs, is crucial in influencing users' motivation and commitment to continue utilising these platforms (Alruwaie et al., 2020). This finding aligns with prior research indicating that performance expectations can significantly influence the continuance intention of a technology (Tam et al., 2020).

The relationship between perceived intelligence and continuance intention in the context of RA is a crucial aspect of user behaviour. Hypothesis 3 identified a strong positive relationship between users' perception of RA's intelligence and their intention to continue using these services (Na et al., 2022). Perceived intelligence refers to users' subjective evaluation of RA platforms' cognitive abilities and decision-making prowess. Previous research on technology adoption and AI acceptance has highlighted the significant role of perceived AI capabilities in influencing users' intentions to continue using AI-based services (Liu et al., 2022). Therefore, RAs that are perceived as highly intelligent can effectively influence users and encourage them to continue using these platforms.

On the other hand, Hypothesis 4 indicated that the perceived likeability of RA is a non-significant factor in driving users' continuance intention (Lee & Chen, 2022). RA are primarily valued for their functional capabilities in automating investment decisions and optimising financial portfolios. The study's findings suggest that users prioritise functional effectiveness over subjective impressions of likeability when evaluating the value and utility of RA platforms. Financial service providers are advised to focus on enhancing RA's functional aspects and perceived benefits rather than solely improving likeability perceptions. This finding contrasts with studies emphasising the importance of affective factors likeability, aesthetics, and emotional appeal in shaping users' attitudes and behaviours towards technology adoption (Kim, 2024). In the context of RA, where competence is paramount, users may prioritise objective performance metrics and functional utility over subjective likeability when assessing financial technology solutions.

Hypothesis 5 in the study identified a positive relationship between perceived safety and continuance intention. The findings suggest that users who perceive RA as safe and secure are more likely to intend to continue using these services. Perceived safety encompasses users' beliefs regarding protecting their personal and financial information, the reliability of the platform's security measures, and the overall trustworthiness of the RA service provider. Safety perceptions are crucial in influencing users' long-term commitment to using RA platforms, as highlighted in previous research on technology adoption and trust (Kadivar, 2015). Studies consistently emphasise the critical role of perceived security and trustworthiness in shaping users' attitudes and behaviours towards digital services (Kar, 2021).

Furthermore, Hypothesis 6 revealed a positive relationship between social outcome expectation and continuance intention. The results indicate that individuals who perceive social benefits or approval from using RA are more inclined to continue using these services. Social outcome expectation refers to users' beliefs about the social acceptance and approval they may receive from peers or society using RA. In financial technology adoption, these perceptions reflect the social influence and normative expectations that influence users' attitudes and behaviours towards adopting and persisting with innovative services (Culver, 2013). Previous studies on technology adoption and social influence underscore the role of social factors, such as peer influence, subjective norms, and social approval, in shaping users' intentions to adopt and continue using new technologies (Cho & Chan, 2021).

6.1. Theoretical implications

The research has significantly contributed to the foundation of theoretical and literature. Firstly, while much of the existing research on RA has primarily focused on adoption intentions, this study has extended the understanding from a continuance intention perspective. By integrating personal, social, and system factors with the Expectation Confirmation Theory (ECT; Oliver, 1980) Cheng (2020), this research has made a valuable addition to the existing theoretical framework. Besides integrating with ECT, this study has integrated the Social Cognitive Theory (SCT; Bandura, 1977) with AI frameworks in the context of RA, providing a more comprehensive outlook for SCT within the technology domain (Cheng, 2022). This integration has expanded the application of SCT beyond its traditional cognitive, environmental, and behavioural factors template to include personal, social, and system factors specific to RA (Xia, 2023). Moreover, the research has filled a significant gap in the literature by combining SCT and ECT within the same framework, offering a more holistic understanding of the variables influencing AI-based RA adoption and continuance intention (Todd & Seay, 2020).

Furthermore, this study has advanced the understanding of RAs literature by exploring the variables related to continuance intention, a dimension that has received limited attention in previous research. By integrating SCT and ECT, this research has enriched the AI-based RA literature knowledge base and provided a more nuanced perspective on the factors influencing users' intentions to continue using these platforms (Northey et al., 2022). Incorporating SCT and ECT has allowed for a deeper exploration of the personal, social, and system factors that shape users' continuance intentions in the context of RA (Yi et al., 2023). Additionally, by combining these two prominent theories, this study has offered a more robust theoretical framework for understanding the dynamics of RA adoption and continuance intention (Ibrahim, 2023). Overall, this research has expanded the theoretical underpinnings of RA adoption and provided a more comprehensive understanding of the factors influencing users' continuance intentions through integrating SCT and ECT. This study has enriched the literature on AI-based RA and laid the groundwork for future research in this evolving field by bridging the gap between personal, social, and system factors.

6.2. Practical implications

This research has integrated the SCT and ECT framework to offer meaningful, practical implications to various financial services providers, policymakers, and researchers. Financial service providers can use the insights provided to enhance the intelligence and safety of the RA. The safety aspects, in particular, proposed the importance of transparent measures and reliable services that users expect from the platform. Cheng (2020) found that reliable and transparent services can improve safety perceptions among AI platforms. Policymakers and financial institutions can develop educational programs to create awareness about the functionalities of RA and focus on creating a better continuance of the RA. These attributes can promote better usage of RA (Xia, 2023). Financial service entities may enhance the social outcome expectations of clients by using the social-cognitive approach to user engagement strategies. Accomplishing this is by ensuring that the RAs application serves its users' needs (Todd & Seay, 2020).

Main Results	Managerial Recommendations
The cognitive ability of RAs is most discussed in the in-depth interviews related to continuance intention.	RA developers and Fintech organisations should emphasise the cognitive capabilities of their RAs in order to increase continuance intention. This practice can include advanced machine learning algorithms, natural language processing, and personalisation features.
Also, self-recognition, self-confidence, and safety are highly discussed in the in-depth interviews related to continuance intention.	Regulatory bodies should consider RA's self-recognition, self-confidence, and safety features and their effects on user decision-making when developing guidelines and policies for the financial services industry. This action can help ensure that RA is designed and deployed in a manner that protects consumer interests and promotes responsible financial decision-making.
Performance Outcome Expectation is the most important factor in developing the continuance intention of RAs.	Continuously monitoring and optimising RA performance outcomes is necessary to build long-term associations. Providers should continuously evaluate the investment performance of the RA and make necessary adjustments in algorithms and asset allocation strategies.
Perceived Intelligence is another important factor in developing the continuance intention of RAs.	Effective marketing and communication strategies are essential for raising awareness and shaping user perceptions of the RAs' intelligence capabilities. Providers should focus on the cognitive and decision-making capabilities of their RAs and how these can benefit users' investment decisions.

Main Results	Managerial Recommendations
Perceived likeability is insignificant in developing the continuance intention of .RAs	Integrating gamification or other motivational features to drive continuance intention might be more effective than .focusing solely on likeability Providers should explore ways to enhance user performance-based engagement beyond just the perceived like-.ability of the RA

Based on the findings, lawmakers may reform regulations required to support the ethical use of AI in financial services. A United Nations report estimates that conflicts could be largely automated because autonomous weapons, particularly drones, could accomplish intelligence-gathering, surveillance, and monitoring with less human-powered products (Yi et al., 2023). To enhance RA platforms to be more innovative and more convenient, financial service providers can find AI experts and tech firms to join them in their journey. Propellers can present to their users products that are competent in the industry and are adaptive to their subscribers' changing needs and preferences (Ibrahim, 2023). Stakeholders can enable the most favourable environment by following the practical implications of the SCT and ECT integration into the RAs domain. Some of the key managerial recommendations arising from the key findings are given in Table 4.

6.3. Limitations and Future Research Directions

This research adopted a cross-sectional design, and the longitudinal data will be able to track the development of tendencies and changes in people over time. However, a holistic idea about the continuance intention is provided in this research. However, a causal relationship between the psychological factors that motivate or resist continuance usage will provide a robust idea about the usage of RAs. This study has administered a qualitative in-depth design in Study 1 to explore the underlying factors with only 33 investors. Future research can administer methodologies such as Netnography designs to discover new variables that decide RA's continuance intentions. Besides, Future longitudinal research would add more value to these frameworks to reveal the dynamic nature of user behaviours and intentions towards RAs platforms. Future studies may focus the research from a cross-cultural perspective, which can build an external context for this research and thus reduce the limitations from that point of view. This research can be extended to various sections of social science research by exploring the effects of continuance intention (Bhattacherjee, 2001) through the lens of psychology, economics, and computer science, which can be transformative in enhancing the comprehension of this phenomenon.

7. Conclusion

This research operates as two studies to explore the factors associated with the continuance intention of RA (study 1) and attempt to understand the impact of the identified variables on the continuance intention (study 2). The findings imply that performance outcome expectation and perceived intelligence are the most significant variables, implying that users prefer the functionality and intelligent architecture of the AI-based RA. The other factors had relatively lesser or no impact on the relationship, emphasising the abovementioned point. The results of this research will provide valuable insights to practitioners and contribute to the theories related to SCT and ECT.

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Appendix A: Indicative Questions during the interview process (Study 1)

Source: Created by authors

How many times have you experienced using robo-advisors (RA) to make financial decisions?

What are some of the personal reasons that continue using RA?

Do you give importance to your evaluations compared to social suggestions in financial decisions?

Do you personally feel RA can increase your productivity?

What is one thing that you like more about RA?

Do you give importance to social suggestions even after your adoption towards RA?

Are you socially driven to continue using the RA?

Which social factor drives you to continue using the RA?

Do you have enough knowledge about how the RA works?

Do you feel that technology is the main reason for the success of the RA?

What is the one thing you like about RA regarding technology?

Would you like to continue using RA?

Why do you think RA is worth using again compared to the other alternatives?

Note: The questions are not necessarily asked in the same order.

Appendix B: Study 1 participant's profile

Participant Code	Gender	Age Bracket	Level of Educa-tion	Number of times used RA	Interview duration
P1	Male	18-25	Bachelors	8	11
P2	Female	26-35	Masters	7	10
P3	Male	Above 45	Masters	6	11
P4	Male	18-25	Bachelors	7	15
P5	Male	26-35	Masters	5	25
P6	Female	18-25	Bachelors	4	19
P7	Male	36-45	Masters	7	9
P8	Male	36-45	Masters	5	16
P9	Female	18-25	Bachelors	12	19
P10	Female	18-25	Bachelors	9	17
P11	Female	26-35	Bachelors	9	9
P12	Female	36-45	Masters	6	12
P13	Male	18-25	Bachelors	8	12
P14	Female	Above 45	Masters	9	9
P15	Female	26-35	Masters	5	18
P16	Male	36-45	Masters	11	13
P17	Female	Above 45	PhD	7	17
P18	Male	18-25	Masters	7	27
P19	Female	26-35	Masters	9	18
P20	Male	26-35	Masters	8	27
P21	Female	36-45	PhD	9	16
P22	Male	Above 45	PhD	4	27
P23	Female	Above 45	Masters	3	22
P24	Female	26-35	PhD	5	10
P25	Female	26-35	Masters	7	13
P26	Male	18-25	Masters	9	20
P27	Female	18-25	Masters	6	11
P28	Male	36-45	PhD	6	21
P29	Male	18-25	Masters	5	18

Participant Code	Gender	Age Bracket	Level of Education	Number of times used RA	Interview duration
P30	Male	18-25	Masters	8	12
P31	Male	18-25	PhD	5	21
P32	Male	36-45	Masters	7	11
P33	Male	26-35	PhD	5	13

Source: Participants profile and table formatted by authors; All participants are from India

Appendix C: Items of the construct used in the study 2.

(Self-Efficacy (Source: Lin and Huang (2008) and rephrased by authors
.My capability to use RAs to finish the job successfully is very high
.My understanding of what to do when using RAs is very high
.My confidence level in using RAs is very high
.My level of comfort in using RAs is very high
.My skill level in using RAs to accomplish the assigned task(s) is very high

Performance Outcome Expectation (Source: Niederhauser and Perkmen (2010) and (rephrased by authors
.RA will increase my effectiveness as an investor
.RA will increase my productivity as an investor
.RA will make it easier for me to make financial decisions

Continuance Intention (Source: Adapted from Balakrishnan and Dwivedi (2021) and (rephrased by authors
.I intend to continue using the services of RAs
I intend to continue using RAs for financial decisions rather than any alternative means
.I intend to continue RAs in future
.I do not intend to discontinue the use of RAs in the future

Social Outcome Expectations (Source: Adapted from Niederhauser and Perkmen ((2010) and rephrased by authors
.Effectively using RA will increase my status in my social circle
.Effectively using RA will increase my social respect among my peers
My colleagues and friends will see me as competent if I effectively use RA for invest-.ment decisions

Perceived Intelligence (Source: Adapted from Bartneck et al. (2009) and rephrased (by authors
.RAs are competent in providing expected financial suggestions
.RAs are knowledgeable in providing expected financial suggestions
.RAs exhibit responsibility while providing expected financial suggestions
.RAs are intelligent in providing expected financial suggestions
.RAs are sensible in providing expected financial suggestions
Perceived Likeability (Source: Adapted from Bartneck et al. (2009) and rephrased (by authors
.I like interacting with RAs during decision-making
.I feel RAs provide friendly suggestions
.RAs exhibit kind interaction during the process
.I feel pleasant working with RAs
.I feel nice working with RAs
Perceived Safety (Source: Adapted from Bartneck et al. (2009) and rephrased by (authors
.I like being relaxed when using the RAs and am not concerned about safety
.I like to be calm when using the RAs and am not concerned about safety
.I like being surprised when using the RAs and am not concerned about the safety
All items are measured on the Five Point Scale: 5 – Strongly Agree to 1 – Strongly .Disagree

دوافع النية المستمرة للمستشارين الآليين في مشهد التكنولوجيا المالية المتطور

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المستخلص:

في السنوات الأخيرة، حظي تقدم الذكاء الاصطناعي وتطبيقاته باهتمام كبير، لا سيما في صناعات مثل التكنولوجيا المالية، حيث يلعب الذكاء الاصطناعي دورًا محوريًا. وقد أدى ظهور المستشارين الآليين (RA) داخل القطاع المالي إلى زيادة هذا النمو. ومع ذلك، في حين أن اعتماد Robo-Advisors آخذ في الارتفاع، إلا أن هناك ندرة في الأبحاث التي تركز على نوايا المستخدمين في الاستمرار على المدى الطويل مع هذه المنصات. لمعالجة هذه الفجوة، استخدم هذا البحث تصميم بحث استكشافي متسلسل مختلط لاستكشاف (الدراسة 1) وتحديد (الدراسة 2) العوامل التي تدفع نية الاستمرارية مع RA القائم على الذكاء الاصطناعي. استخدم البحث النظرية المعرفية الاجتماعية (SCT) لتطوير نموذج مفاهيمي يتضمن العوامل الشخصية والاجتماعية والنظامية. ومن خلال تحليل شمل 425 مستثمرًا، كشفت الدراسة أن الأداء والذكاء ظهرا كمحركين أساسيين لنية الاستمرار مع Robo-Advisors. من خلال دمج SCT مع الأدبيات الموجودة حول القرارات المالية القائمة على الذكاء الاصطناعي، يساهم البحث بشكل كبير في أدبيات SCT. علاوة على ذلك، تقدم الدراسة رؤى قيمة للممارسين في الصناعة المالية.

الكلمات المفتاحية:

مستشار روبو؛ النظرية المعرفية الاجتماعية. نية الاستمرار؛ الذكاء الاصطناعي؛ السلامة المتصورة؛ الكفاءة الذاتية.