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Influential Factors of AI Advisor Adoption in Consumer Finance

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ABSTRACT

The development of artificial intelligence (AI) in consumer finance has given rise to robo-advisors, automated platforms offering investment guidance and portfolio management. Despite their potential for cost efficiency, accessibility, and objective decision-making, adoption and use remain uneven, with trust and user experience cited as critical determinants. This study investigates the factors influencing individual use intention of robo-advisors, focusing on trust, user satisfaction, perceived usefulness, and perceived ease of use. Drawing on theories and empirical evidence, a survey was conducted with 113 participants, primarily millennials and Gen Z, to capture contemporary attitudes toward AI-driven financial services.

Descriptive and inferential analyses reveal that trust, satisfaction, and perceived usefulness significantly predict use of robo-advisors, while perceived ease of use does not exert a significant influence, likely reflecting the tech-savvy profile of respondents. Within trust, competence and data security were most highly rated, whereas transparency and algorithmic fairness emerged as areas for improvement. These findings align with previous literature on FinTech adoption, emphasizing the centrality of trust and the importance of clear, actionable guidance and platform transparency.

The study provides insights into what influence use intention of individual customers in a robo-advisory context and addresses literature gaps concerning empirical evidence on trust, satisfaction, and use in AI-driven consumer finance. Practically, it provides insights for providers to enhance user engagement through improved transparency, explainability, and user experience. Future research suggestions are longitudinal and multi-platform studies to further explore adoption dynamics.

Keywords: Robo-advisors, AI in finance, Trust, User satisfaction, Perceived usefulness

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Chapter 1 Introduction

1.1. Research Background

Within the past 20 years, artificial intelligence (AI) has brought considerable value and innovation in financial services, shifting roles that include credit scoring, fraud detection, investment suggestions, and portfolio management (Davenport and Ronanki, 2018). The emergence of machine learning, big data analytics, and natural language processing has contributed to this trend because it makes the financial industry more ready to embrace AI-based automation and personalisation of services (Jagtiani and Lemieux, 2019). An interesting example of AI in consumer finance is the creation of robo-advisors, online services that deliver automated, customised investment guidance and portfolio management services with limited human intervention employing the techniques of algorithms (Buchanan, 2019). They gather user information, including financial goals, risk tolerance, and time horizons, and then utilise portfolio optimisation algorithms in order to allocate and rebalance an investment portfolio, generally low-cost exchange-traded funds (Jung et al., 2018).

Robo-advisors have gained significant popularity in both user adoption and assets under management (AUM) since the launch of early entrants such as Betterment and Wealthfront in the United States in 2008 (Helms et al., 2022). The industry has since expanded rapidly, positioning robo-advisors as a convenient substitute to traditional human financial advisors (Phoon and Koh, 2018). In addition, they are available 24 hours a day through digital applications (Belanche et al., 2019). Moreover, AI advisors are becoming increasingly favourable in consumer finance because they combine efficiency, accessibility, and personalisation in ways that traditional advisory services often cannot (Isaia and Oggero, 2022). Unlike human advisors, who may be limited by cognitive or capacity, AI-powered systems can process and analyse vast amounts of financial and market data in real time. As a result, robo-advisors can generate recommendations that are not only tailored to individual goals but also immediately responsive to changing economic conditions (Tan, 2020).

The rise of robo-advisors was partly a response to the 2008 global financial crisis, which eroded trust in traditional financial institutions and created demand for transparent, low-cost alternatives for better objectivity and automation (Arner et al., 2016). Initially targeting younger, tech-savvy investors, many robo-advisors expanded their offerings to include hybrid models combining automated algorithms with services provided by human (Isaia and Oggero, 2022; Brenner and Meyll, 2020). With the rise of many choices of robo-advisor products, the market has also seen consolidation, with large financial institutions acquiring or launching their robo-advisory platforms to compete with early disruptors (Bhatia et al., 2020). This trend reflects both the maturation of the industry and the recognition by incumbents of the value that automated advisory services bring to consumer finance.

In the wider context of AI in consumer finance, one example is Rogo AI, which is targeted at institutional workflows, as opposed to retail investors. Rogo AI is a safe, generative-AI-enabled space where people can perform activities like financial analysis, deal preparation and report automation (Financial Times, 2025). The cloud-based framework relies on the industry-recognised security standards and has been trusted by the largest investment enterprises by incorporating financial data sources (such as the S&P Capital IQ) and AI-based models that assist with making decisions. In 2024, Rogo AI raised USD 50 million at Series B and the company was valued at USD 350 million, indicating that investors are confident in the scalability of the financial tools developed using AI (FinTech Global, 2025). Although Rogo AI exist in the institutional domain, its adoption process, especially when it comes to trust, explainability, and perceived value, is also similar to those of consumer-centric robo-advisors. Thus, studying Rogo AI alongside consumer-level platforms offers an opportunity to explore both individual and organisational adoption patterns.

1.2. Research Problem and Rationale

In spite of their ascribed advantages, there is still a high degree of adoption barriers, and most of them pertain to trust, which is considered a paradox of fintech adoption (Dimitrova et al., 2022). Early adopters valued algorithmic decision-making because it appeared less biased and more rules-based (Phoon and Koh, 2018). However, there is a higher awareness of issues, including the lack of transparency in algorithm-based decision-making, data privacy, and the lack of a human decision (Belanche et al., 2019; Anagnostopoulos, 2018). The trust towards AI systems consists of both rational and emotional components, as not only do users need to believe in the ability and reliability of the system, but also feel that it has their best interests (Cheng, 2023). It is worth noting that while there is a substantial body of research on trust in AI technologies, much of it has been conducted in broad contexts such as general AI applications (Dwivedi et al., 2021), AI-driven services (Montealegre-López, 2025) or within fintech more widely (Gomber et al., 2018). However, robo-advisors as a distinct category of AI-driven financial services remain under-researched. This is significant because the nature of robo-advisory services requires consumers to delegate high-stakes, future-oriented financial decisions to algorithms, which raises unique concerns around benevolence, integrity, and competence. The limited empirical studies on robo-advisors leave an important gap in understanding how trust dimensions, user satisfaction, and demographic factors interact to shape adoption intentions.

Furthermore, the rapid pace of AI innovation means that much of the literature may already be outdated, especially given recent advancements in generative AI and explainable AI (Piotrowski and Orzeszko, 2023). Thus, this research is conducted to capture the most recent attitudes of individual users towards the use of robo-advisors in consumer finance to contribute to theses literature gaps and provide practical insights on how to design, market, and scale robo-advisory services.

1.3. Research Aims and Objectives

This research addresses these gaps by examining the relationship between trust, satisfaction, and use of robo-advisors, using a mixed-method approach that combines a consumer survey with a case study of Rogo AI. The rationale is twofold. Firstly, it is expected that findings from the research can contribute to academic understanding of technology adoption in financial services by integrating constructs from technology adoption theories with trust and satisfaction variables. In addition, it aims to provide practical insights for fintech developers and financial institutions seeking to improve the design, marketing, and adoption of robo-advisory services.

Research objectives of the research are set as follows:

- To identify factors that facilitate or hinder the use of robo-advisors
- To illustrate these dynamics through a case study of Rogo AI in the institutional finance context.

Research question that this research is carried out to answer is: What factors influence consumer intention to use robo-advisory services?

1.4. Structure of the Dissertation

Chapter 1 - Introduction provides background on AI in consumer finance, the rise of robo-advisors, outlines the research problem, rationale, objectives, research questions, scope, limitations, and structure. Chapter 2 reviews the evolution of AI and robo-advisors, key technology adoption theories and literature on determinants of AI adoption, highlighting research gaps. Chapter 3 presents the theoretical framework of the research. In addition, Chapter 4 Methodology provides details on the positivist, deductive research design, the case study of Rogo AI, survey methods, sampling strategy, analytical techniques (descriptive statistics, reliability analysis, regression), and ethical considerations.

Chapter 5 presents the results of the demographic profile of respondents, descriptive and inferential analysis of key variables, and findings from regression analyses. In addition, findings are interpreted in light of existing literature, discuss the role of trust dimensions and satisfaction in adoption, and integrate insights for the case of Rogo AI. Finally, Chapter 6 provides the summary of the findings, research limitations, and areas for future research.

Chapter 2 Literature Review

2.1. Theoretical Background

The Davis (1989) Technology Acceptance Model (TAM) has gained a lot of attention in researches that focused on technology adoption due to its parsimoniousness and predictive ability. It maintains that two cognitive perceptions have been identified to be the main determinants of the intention of a user to adopt technology, namely, Perceived Usefulness and Perceived Ease of Use. The former is concerned with the confidence people have in a technology as increasing the performance, whereas the latter is concerned with how confident people feel regarding effortlessness to use a system. These in turn determine the attitude to utilise the technology and the subsequent behavioural intent (Davis, 1989; Venkatesh and Davis, 2000). In a robo-advisory setting, PU may be transformed into the beliefs regarding the ability of the system to provide competitive returns in the investment activity or enhance the process of financial decision-making, whereas PEOU may be involved in a similar relation to usability of the platform and its comfort level. Among the main advantages of TAM that make it widely appealing, there is an empirical robustness of this theory across many areas, including FinTech application or clear, measurable constructs, etc. In the case of robo-advisor research, the focus on perceived usefulness will also be specifically essential since investment decisions and perceptions of performance benefits seem to be critical, and ease of use plays a fundamental part in contexts of promoting adoption to investors with lower technological fluency. TAM has, however, been under steady criticism as to being excessively reductionist, focusing intensively on cognitive beliefs, at the expense of emotional, social, and contextual considerations. It presumes a rational decision-making process to a large extent and trust, perceived risk, and regulatory environment, which are highly paramount in financial services, does not reflect it. Besides, the theory fails to explain how different perceptions can vary over a long time as the users become more familiar with the technology which is especially applicable in robo-advisors as more frequent use of the service can modify the attitudes (Solberg et al., 2022).

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), sought to address some of TAM's limitations by integrating constructs from eight different models of technology acceptance. The later extension, UTAUT2, adapts the model for consumer contexts by adding Hedonic Motivation, Price Value, and Habit (Venkatesh et al., 2012). In robo-advisory adoption studies, UTAUT2 is advantageous because it captures broader social and experiential dimensions: for example, the influence of peers' recommendations, the perceived affordability of services, or the habitual integration of the platform into daily financial routines. The strength of the model is the comprehensiveness of the model as well as flexibility that renders the model more contextually sensitive than TAM. In the case of robo-advisors, Hedonic Motivation could be a factor in adoption by those investors who are younger and tech-savvy and enjoy communicating with digital technology, whereas Price Value would be particularly important in a market where low fees are a principal selling point. UTAUT2 has, however, been criticised as being too complex and risking overfitting; the amount of constructs and moderators considered can make it empirically unwieldy and result in inconsistent results across time. Besides, although UTAUT2 recognizes the importance of social influence, its ability to downplay affective trust and perceived risk cannot be ignored as they are the most critical financial choice concerns when the degree of uncertainty and information asymmetry are very high.

2.2. Empirical Evidence

A growing stream of quantitative work shows that constructs inherited from TAM and UTAUT consistently predict intention to use robo-advisors. Studies in large emerging markets report that perceived usefulness/performance expectancy and perceived ease/effort expectancy exert sizeable, direct effects on behavioural intention, with social influence often contributing additional variance; these results replicate in samples of active retail investors as well as broader consumer panels (Solberg et al., 2022; Venkatesh et al., 2012; Jagtiani and Lemieux, 2019). Recent field evidence from the Indian stock market, for example, uses TAM/UTAUT constructs and finds performance and effort beliefs as primary drivers of adoption, even after accounting for demographic and experience controls (Venkatesh et al., 2012).

Trust can be seen consistently as the cornerstone antecedent across markets. Mixed-methods in the context of the U.S. financial specialists and customers demonstrates that the perceived integrity/competence of the provider and perceived data security predict satisfaction and further usage, the latter conditioned by a partial mediating position of trust between those qualities and satisfaction (Chou et al., 2023; Siau and Wang, 2018). The increased level of trust in that study implied an increased level of self-reported retention, recommendation intentions, and increased readiness to unify assets with a single platform (FPA, 2024). Such results concur with Asia based studies that found trust has a direct prediction on intention and that its effect remains tight even when we control on technology anxiety and satisfaction with the current advisory arrangements to indicate that in the case of a strong trust, perceived risks are reduced (Gefen et al., 2003; Pavlou, 2003).

A second reliable theme is the uncertainty-reduction pathway. In a structural model grounded in value-based adoption, clear uncertainty-reduction strategies, transparent fee disclosures, performance reporting, and explanation of portfolio construction translate into stronger investment intentions via elevated perceived value and reduced perceived risk (Chen and Dubinsky, 2003). The authors show that perceived diagnosticity of the platform's information (how decision-useful it feels) underpins these gains, reinforcing the role of explainability and auditability in financial AI (Frank et al., 2023).

There are a number of studies which evaluate satisfaction as a mediating variable between trust and the behavioural intention of the user, which entails the quality and experience scrutiny that the user puts on the service after the adoption process. Based on Expectation-Confirmation Theory (ECT), empirical evidence in the use of digital banking has demonstrated that satisfaction reinforces the chances of the sustained usage when performance of service provided exceeds or matches the expectation of users (Bhattacherjee, 2001; Chan et al., 2022). Arenas-Parra et al. (2024) have found out in robo-advisor settings that the satisfaction with the investment-performance requirement and the user interface design have a significant impact on the prediction of proceeding using an intention in South Korea. Notably, satisfaction can be contingent on returns, yet it is always predicated on how easy to use, the responsiveness of the customer service, and how personalised the investment advice feels (Belanche et al., 2019). It is consistent with the results by Beak and Kim (2023) who found that, despite similar returns, robo-advisors with more understandable performance charts and more intuitive dashboards scored higher in terms of satisfaction and more likely to remain in the client.

Finally, a set of literature reviews and multi-country analyses converge on two practical implications. First, trust formation is multi-layered, spanning technology (model quality, explainability), firm-specific (brand reputation, service recovery), and system-level elements (regulation, certification) (Granulo et al., 2021). Second, satisfaction appears to act as a conduit from beliefs to intention and use; in the robo context, satisfaction is co-produced by perceived returns, quality of explanations, and frictionless support, which together sustain usage beyond initial novelty (Ruan and Mezei, 2022). These syntheses also underscore persistent gaps: a shortage of longitudinal evidence, limited experiments in real brokerage settings, and scant attention to the interaction between objective vs. subjective literacy and trust under volatility.

Chapter 3 Conceptual Framework

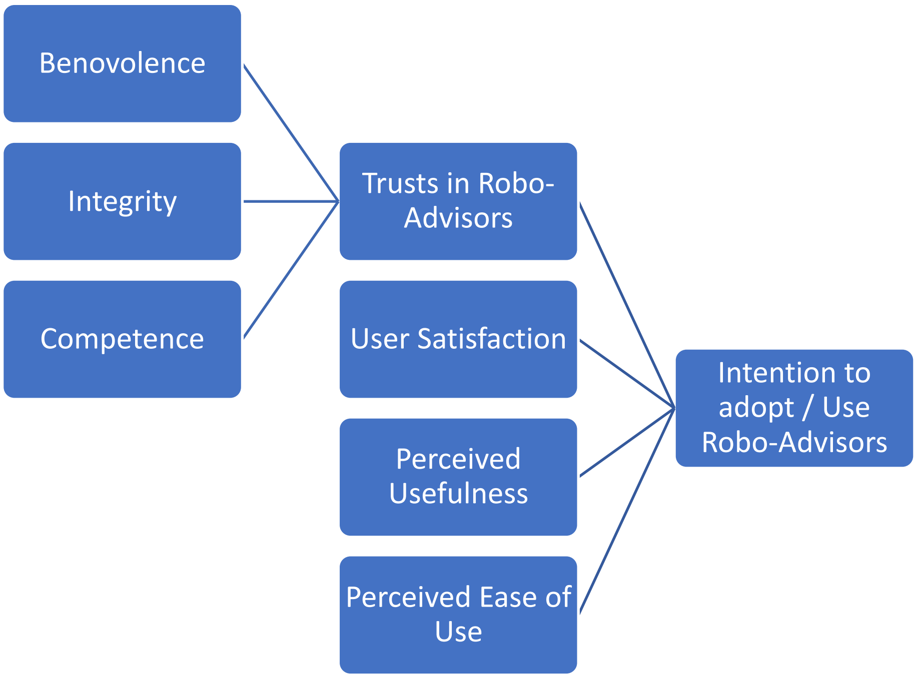
This study draws on established models of technology adoption and trust to examine the determinants of consumers' intention to use robo-advisors. Trust is conceptualised in this study through three dimensions: benevolence (the belief that the robo-advisor acts in the user's best interests), integrity (adherence to ethical and transparent practices), and competence (technical capability and financial expertise). These dimensions align with Mayer et al. (1995) integrative model of organisational trust, which has been widely applied in e-commerce and fintech contexts. In robo-advisory services, users often lack the technical knowledge to fully evaluate algorithms, making trust a substitute for direct performance verification (Lankton et al., 2015). Additionally, this framework incorporates customer satisfaction as an intermediary variable, consistent with the Expectation-Confirmation Model (Bhattacherjee, 2001). Satisfaction is shaped by whether the service meets or exceeds prior expectations, influencing the intention to continue using or recommending the service. In financial technology adoption, satisfaction not only reflects functional performance but also emotional reassurance, particularly in volatile market conditions (Lee and Moray, 1992).

While there is is a growing body of research on AI adoption in consumer finance, most existing studies focus on general FinTech platforms or digital banking, rather than robo-advisors specifically (Belanche et al., 2019; Montealegre-López, 2025). Robo-advisors represent a unique intersection of automated decision-making, investment risk, and user trust, yet empirical evidence on individual adoption behavior, particularly in relation to trust, satisfaction, and perceived usefulness, remains limited (Jung et al., 2018; Isaia and Oggero, 2022). By targeting these constructs within a sample of potential and current users, this research fills a gap in the literature, providing updated, context-specific insights into adoption drivers and barriers in AI-based financial advisory services.

Although the survey primarily measures cognitive perceptions such as trust, satisfaction, usefulness, and ease of use, it can indirectly capture affective responses through trust and satisfaction dimensions. Prior research suggests that emotional responses, such as confidence, perceived security, and satisfaction, are intertwined with cognitive evaluations and influence adoption behavior (Gefen et al., 2003; Siau and Wang, 2018). For example, higher trust can evoke feelings of security and reduce perceived risk, which in turn increase the likelihood of adopting and recommending a platform (Granulo, et al., 2021; Chou et al., 2023). Similarly, satisfaction reflects an evaluative-emotional state based on the congruence between expectations and experience (Ruan and Mezei, 2022).

Finally, there is a lack of integrated models that combine technological acceptance variables with behavioural finance perspectives in the same empirical framework. This study bridges a disconnect between theoretical models which primarily focus on cognitive determinants, and actual user adoption behaviors that also involve affective or emotional dimensions.

The conceptual framework of the research is shown below.



Chapter 4 Research Methodology

4.1. Research Design

This study adopts a positivist research philosophy, which follows the assumption that social reality is objective (Saunders et al., 2023). In addition, there is an assumption that social constructs can be quantified and measured (Bell et al., 2022). Positivism is applicable in this study because of the objective of this study which is to examine quantitatively the variables that affect the use of robo-advisors. It presupposes that these relationships should be located with the assistance of statistical analysis and that the obtained results could be generalised to a broader population of people who could become potential and current users of robo-advisory platforms (Creswell and Creswell, 2018; Blaikie and Priest, 2019).

A deductive research approach is adopted, consistent with the hypothesis-driven nature of the study. Deductive reasoning begins with established theory and derives specific hypotheses to test empirically using survey data (Ghauri et al., 2020). This approach is appropriate because the study seeks to test predefined relationships between independent, thereby contributing to theory validation in the context of robo-advisory uses.

This study adopts a quantitative research strategy to investigate the relationships of the social constructs, while also considering demographic influences such as age, gender, income, and education. The quantitative approach is selected because it enables the systematic measurement and statistical analysis of constructs, facilitating hypothesis testing and generalisation of findings (Creswell and Creswell, 2018). Quantitative research is particularly appropriate in technology adoption contexts for several reasons. First, it allows for the use of validated measurement scales, enabling the constructs of trust, satisfaction, and behavioural intention to be operationalised consistently across respondents (Creswell and Creswell, 2018). This is critical in fintech research, where perceptions and behavioural drivers may vary across user segments. Second, the quantitative strategy supports the application of inferential statistical techniques, such as regression analysis or structural equation modelling, to identify the strength and direction of relationships between variables. This aligns with the study’s objective of testing theoretically derived hypotheses grounded in the Technology Acceptance Model (TAM) and trust-based adoption theories.

The research also employs a case study strategy focusing on Rogo AI, a prominent AI-powered robo-advisory platform. The case study approach allows for an in-depth exploration of the adoption factors within a real-world organisational and technological context, while maintaining focus on generalisable relationships (Yin, 2018; Gray, 2014). The case is complemented by survey data collection to quantitatively measure users' perceptions and behavioural intentions. This combination enables a more robust understanding of both the organisational context and individual user-level factors influencing adoption (Saunders et al., 2023).

4.2. Data Collection

The primary data are obtained through a structured survey, which is a questionnaire conducted among potential or current users of the robo-advisor. Surveys allow the researcher to reach a broad group of respondents across different demographic categories, such as age, gender, education, and financial literacy. Given that the adoption of robo-advisors may vary by these characteristics, a survey enables efficient capture of heterogeneity in perceptions and behaviours (Fowler, 2014). In addition, By using closed-ended questions and standardised rating scales, surveys ensure that all respondents are presented with the same questions in the same format. This consistency enhances measurement reliability and reduces bias, allowing for valid comparisons across individuals (Dillman et al., 2014).

Variables

The significant variables to be measured by the questionnaire are the trust (benevolence, integrity, competence), user satisfaction, perceived usefulness, perceived ease of use, willingness to adopt/intention to use. To measure trust has been scaled with validated measures based on previous literature (research on FinTech adoption) which was later followed by satisfaction and adoption intention scales that were based on the existing literature TAM and UTAUT2 scales (Venkatesh et al., 2012). The five-point Likert scale provided in the questionnaire (i.e., ranging between 1 (Strongly Disagree) and 5 (Strongly Agree) enables standardised and measurable answers as well as statistical analysis (Creswell and Creswell, 2018).

Trust is conceptualised as a multi-dimensional construct comprising benevolence, integrity, and competence, following McKnight et al. (2011). Benevolence refers to the user's belief that the robo-advisor acts in their best interest and considers their financial well-being. Integrity reflects the perception that the platform adheres to ethical standards, communicates honestly, and maintains transparency in its operations. Competence captures the user's confidence in the robo-advisor's technical and financial abilities, including its capacity to provide accurate and reliable investment recommendations. These three dimensions collectively influence satisfaction and intention to adopt new technologies which have been established in previous studies (Siau and Wang, 2018). This research will examine whether the relationships still hold in the case of users of robo-advisors.

Intention to use serves as the primary dependent variable in the study, reflecting the likelihood that a respondent will adopt or continue using a robo-advisor in the near future. This construct draws from TAM and UTAUT2, where behavioural intention is a strong predictor of actual usage (Davis, 1989; Venkatesh et al., 2003). Survey items assess willingness to use, readiness to switch from human advisors, and likelihood of recommending the platform to others, capturing both proactive adoption and word-of-mouth intentions.

The user satisfaction measure is the extent to which user expectations and needs are fulfilled as they are perceived against robo-advisor platform. Based on the literature of information systems and marketing, satisfaction consists of perceptions in terms of usability, usefulness of recommendations, control of financial decisions and summation of experience (Fornell et al., 1996; Oliver, 1980). Satisfaction is regarded as a mediating variable that draws the correlation between trust and perceived usefulness and behavioural intention since the satisfied users seem to keep using the service and tell others about it (Bhattacherjee, 2001).

Sample and sampling method

The target sample for this research consists of tech-savvy customers Millennium, and Gen-Z who are more likely to interact with digital financial technologies as well as robo-advisory services (Isaia and Oggero, 2022). To achieve that it uses purposive sampling technique, meaning that the respondents should be related to experience or interest in the digital investment platforms, but additional respondents should be reached with the help of snowball sampling to find more people within the circle of initial respondents (Ting et al., 2025). The intended sample size is 150; this is sufficient enough to conduct a multiple regression analysis since there will be a possibility of estimating a relationship between a dependent and independent variable with high confidence since it is probable that some respondents may never complete the responses (Saunders et al., 2023).

The survey is also intended to be mainly sent out via social networks like Facebook with the opportunity to online forums of interest and personal network sharing. It was based on the necessity to reach a large and diverse population of potential and current robo-advisor users and geographically wide in a short period of time and budget. There are some benefits of social media use in the distribution of surveys in the fintech adoption research. First, they allow targeting a large audience and diversity. With LinkedIn, people have access to financially literate people and technology adopters, whereas Facebook and X have access to a broader section of the population, in terms of age brackets as well as educational levels. This variety can be considered worth considering in terms of demographic impacts on trust, satisfaction, and intention to use robo-advisors, including age, gender, and education. Second, the collection of data through the use of social media is very fast and cheap. The survey link may be posted and reposted in the appropriate communities (such as fintech discussion channels, investment clubs), which makes it possible to resort to snowball sampling and, perhaps, extend the sample within the shortest time range (Bell et al., 2022). Such efficiency is especially relevant in the fintech sector, where the perceptions of the users can change relatively fast based on updates in the technology, events in the market, or regulatory interventions.

4.3. Data Analysis

Descriptive and inferential statistics will be combined in the analysis of the collected data. Means, standard deviations, and frequency distributions will result in the portrayal of descriptive data about participant demographics and central tendencies of the major variables (Creswell and Creswell, 2018; Ghauri et al., 2020). To evaluate the internal consistency of multi-item scales, the reliability analysis based on Cronbach alpha will be conducted to make sure that such constructs as trust and satisfaction are reliably measured (Hair et al., 2022). The test of the hypothesised relationships between independent variables will be carried out through multiple regression analysis to enable the following of the effect-sizes and the statistical significances (Field, 2017).

4.4. Ethical Considerations

Ethical integrity is central to the research including the informed consent and voluntary participation (Babbie, 2021). Data privacy is ensured through anonymisation of responses and secure storage in password-protected systems, in compliance with data protection regulations. Finally, the study will obtain institutional ethics approval prior to data collection, ensuring that all research procedures meet recognised ethical standards for studies involving human participants (Trochim et al., 2022).

Chapter 5 Findings and Evaluation

5.1. Sample Demographics

There are 113 respondents taking part in the survey with the following demographic profile.

Table 1: Demographic Profile of Survey Respondents

Demographic Variable	Category	Frequency	Percent
Gender	Male	42	37.2%
	Female	62	54.9%
	Non-binary	5	4.4%
	Prefer not to say	4	3.5%
Age Group	18–24	18	15.9%
	25–34	39	34.5%
	35–44	34	30.1%
	45 or older	22	19.5%
Education	Secondary school or equivalent	8	7.1%
	College diploma / vocational training	24	21.3%
	Bachelor's degree	42	37.2%
	Master's degree	28	24.8%
	Doctorate (PhD)	18	15.9%
	Prefer not to say	1	0.9%
Current use of Robo-Advisors	Yes	60	53.1%
	No	53	46.9%
Financial Literacy	Very low	8	7.1%
	Low	36	31.9%
	Moderate	31	27.4%
	High	27	23.9%
	Very high	11	9.7%

In terms of genders, females represent the highest proportion (54.9%), followed by males (37.2%). Non-binary (4.4%) and "prefer not to say" (3.5%) are much smaller. The 25–34 group is the largest (34.5%), closely followed by 35–44 (30.1%), making these two groups similar and together accounting for nearly two-thirds of respondents. The largest group holds a bachelor's degree (37.2%), followed by master's degree holders (24.8%) and vocational/college diploma (21.3%).

Users slightly outnumber non-users (53.1% vs. 46.9%), making it fairly balanced. This suggests that the findings reflect both experienced and potential users, allowing for insights into both barriers and current use of robo-advisors. Self-assessed financial literacy was generally moderate to high: 27.4% rated themselves as moderate, 23.9% as high, and 9.7% as very high, while lower literacy levels were less represented (7.1% very low, 31.9% low). This distribution implies that the sample is reasonably financially informed, which may influence trust and satisfaction with robo-advisory services.

Overall, the sample appears reasonably representative of a tech-savvy, financially literate population, particularly among younger adults, who are a key demographic for robo-advisor adoption. The relatively balanced mix of users and non-users, combined with moderate-to-high financial literacy, provides a suitable basis for examining attitudes, trust, and intentions regarding robo-advisory services.

5.2. Descriptive Analysis Of Key Variables

This table presents the statistics for respondents' perceptions of trust across six items related to robo-advisors.

Table 2: Descriptive Statistics – Trust in Robo-Advisor

Item	N	Minimum	Maximum	Mean	Std. Deviation
I believe AI-powered robo-advisors make decisions that are in my best interest (trust_1)	113	1	5	3.75	1.229
I trust the accuracy of investment recommendations (trust_2)	113	1	5	3.77	1.142
I believe robo-advisors are transparent about how they operate (trust_3)	113	1	5	3.62	1.284
I am confident that my personal financial data is secure (trust_4)	113	1	5	3.73	1.248
I believe AI algorithms are fair and unbiased (trust_5)	113	1	5	3.73	1.248
I would trust a robo-advisor as much as a human advisor (trust_6)	113	1	5	3.98	1.157

Overall, mean scores for trust items range from 3.62 to 3.98, indicating moderate to relatively high trust among respondents. The highest mean (3.98) relates to trust equivalence with human advisors, suggesting that users may increasingly accept AI advice as comparable to traditional services. However, transparency (mean 3.62) scores lowest, highlighting that perceived opacity in algorithms remains a concern, which aligns with prior literature on AI adoption barriers in finance. The standard deviations (1.142–1.284) indicate considerable variation in responses, reflecting heterogeneous perceptions of trust, possibly influenced by prior experience, financial literacy, or demographic factors.

This table summarizes respondents' satisfaction levels across five items.

Table 3: Descriptive Statistics – User Satisfaction with Robo-Advisors

Item	N	Minimum	Maximum	Mean	Std. Deviation
Using robo-advisors makes managing my investments easier (satisfaction_1)	113	1	5	3.90	1.118
I feel satisfied with the overall experience (satisfaction_2)	113	1	5	3.88	1.135
Robo-advisors provide helpful explanations of recommendations (satisfaction_3)	113	1	5	3.82	1.241
I feel in control when using robo-advisors (satisfaction_4)	113	1	5	3.90	1.187
My expectations were met when using or learning about robo-advisors (satisfaction_5)	113	1	5	3.94	1.159

Satisfaction scores are slightly higher than trust scores, with means between 3.82 and 3.94. Respondents generally **feel positive about usability and meeting expectations**, suggesting that satisfaction is influenced more by the experience of interaction than underlying trust in algorithms. The smallest mean (3.82) relates to the clarity of recommendations, highlighting a potential area for improving **explanatory transparency**. Standard deviations around 1.1–1.2 suggest moderate response variability.

This table presents descriptive statistics for three items measuring how easily respondents can use robo-advisors.

Table 4: Descriptive Statistics – Perceived Ease of Use

Item	N	Minimum	Maximum	Mean	Std. Deviation
Robo-advisors are easy to navigate and operate (ease_1)	113	1	5	3.96	1.068
Learning how to use a robo-advisor is straightforward (ease_2)	113	1	5	3.63	1.174
I do not need technical knowledge to benefit from a robo-advisor (ease_3)	113	1	5	3.75	1.229

Ease of use scores suggest respondents **generally find robo-advisors user-friendly**, particularly in terms of navigation (mean 3.96). However, learning the system scored lower (3.63), indicating that **initial adoption may still require effort or guidance**, especially for users with lower technical proficiency. The variation (SD 1.068–1.229) again signals differences in user comfort and experience, possibly influenced by prior exposure to digital finance platforms.

This table summarizes respondents' perceptions regarding the usefulness of robo-advisors in managing their investments and financial decisions.

Table 5: Descriptive Statistics – Perceived Usefulness of Robo-Advisors

Item	N	Minimum	Maximum	Mean	Std. Deviation
Robo-advisors help me make better financial decisions (useful_1)	113	1	5	3.78	1.155
I find robo-advisors useful for managing my investment portfolio (useful_2)	113	1	5	4.00	1.094
Robo-advisors save me time in financial planning (useful_3)	113	1	5	3.89	1

The mean scores for perceived usefulness items range from 3.78 to 4.00, indicating that respondents generally perceive robo-advisors as **helpful and practical tools** for financial decision-making. Standard deviations (1.080–1.155) suggest moderate variability in responses, implying that while most respondents see utility in robo-advisors, individual experiences or expectations vary, likely influenced by prior use, familiarity with financial technology, and financial literacy levels.

From the descriptive analysis, it can be seen that Trust remains moderate, with transparency and algorithmic fairness as key barriers. This supports previous findings that trust is a decisive factor in AI adoption in financial services. Ease of use is perceived positively, yet onboarding challenges indicate that even tech-savvy users may require guidance, highlighting the importance of design and educational support. Overall, these descriptive statistics show that while users are increasingly open to adopting robo-advisors, barriers related to trust, understanding, and perceived transparency remain, emphasizing the need for targeted interventions in design, communication, and education.

5.3. Regression Analysis

Table 6 presents the results of the regressionn analysis examining the predictors of adoption of robo-advisors among 113 respondents. The independent variables included trust, satisfaction, perceived usefulness, and ease of use, while the dependent variable was respondents' intention to use robo-advisors.

Table 6: Multiple Regression Predicting Adoption of Robo-Advisors

Predictor	B	SE B	β	t	p
Constant	0.893	0.330	—	2.705	.008
Trust	0.331	0.085	0.335	3.890	<.001
Satisfaction	0.209	0.091	0.212	2.306	.023
Usefulness	0.223	0.092	0.221	2.417	.017
Ease of Use	0.079	0.068	0.095	1.166	.246

The regression analysis shows that trust ($\beta = 0.335$, $t = 3.890$, $p < .001$) is the strongest predictor of adoption, indicating that respondents has a higher chance of using robo-advisors when they perceive the system as reliable, fair, and acting in their best interest. Satisfaction ($\beta = 0.212$, $t = 2.306$, $p = .023$) and perceived usefulness ($\beta = 0.221$, $t = 2.417$, $p = .017$) also significantly predict adoption, demonstrating that users who are satisfied with their experience and recognize tangible benefits from using robo-advisors have a higher tendency for the use of the technology. In contrast, ease of use ($B = 0.079$, $\beta = 0.095$, $t = 1.166$, $p = .246$) was not a significant predictor, suggesting that while users generally find the platforms easy to navigate, ease of use alone does not directly influence adoption decisions in this sample.

The p-values for trust, satisfaction, and usefulness are below the conventional threshold of .05, indicating that the observed relationships are statistically significant. Ease of use, with a p-value above .05, does not show a statistically meaningful relationship with adoption. These findings are consistent with technology acceptance research, where perceived benefits, user satisfaction, and trust are critical determinants of adoption behavior, whereas navigational simplicity may support usage but is not sufficient to drive adoption on its own. Overall, the results demonstrate he importance of fostering user trust, ensuring positive experiences, and demonstrating clear value to encourage adoption of robo-advisors, while addressing transparency and explanatory clarity to further enhance user confidence.

5.4. Discussion of Findings

The results of this study corroborate a growing body of literature demonstrating that constructs inherited from the theories consistently predict the intention to use robo-advisors. Specifically, perceived usefulness and performance expectancy emerged as significant predictors of adoption in our sample, aligning with previous studies, where performance and effort beliefs were the primary drivers of adoption, even after controlling for demographics and prior experience (Venkatesh et al., 2012, Jagtiani and Lemieux, 2019). In the survey, perceived usefulness demonstrated a significant positive relationship with adoption, emphasizing that respondents are more likely to adopt or use robo-advisors when the technology provides tangible benefits such as improved financial decision-making and time savings.

Consistent with previous studies, the strongest factor that predicts the adoption of the AI-mediated financial services in the study was the trust that emphasizes the importance of this variable (Gefen et al., 2003; Pavlou, 2003; Morgan and Hunt, 1994; Siau and Wang, 2018). The survey data indicated that one could characterize the degree of trust the respondents demonstrated towards robo-advisors as fairly high, especially in the context of the soundness of AI algorithms applied to make decisions in comparison to human advisors. This confirms reports of other multi-country research that perceived integrity, competence and data security are predictive of user satisfaction and intention-to-use (FPA, 2024). The Rogo AI case has situational relevance: being a new financial AI platform, Rogo has focused on high-quality fee disclosure, straightforward portfolio descriptions, and reporting on performance that provided the context of the case and might have led to respondent perception of trust. This result is consistent with the uncertainty-reduction pathway found in the literature, in that further transparent disclosures, explainability, and auditability reduce the perceived risk and enhance adoption intentions (Tan, 2020).

Satisfaction was also a significant predictor of adoption, reflecting its role as a mediating mechanism between beliefs and behavioural intention (Bhattacherjee, 2001; Chan et al., 2022). Respondents reported moderate to high satisfaction with their robo-advisory experiences, including ease of managing investments, clarity of recommendations, and perceived control over financial decisions. This supports findings from South Korea and broader digital banking contexts, where satisfaction reinforces sustained usage and is contingent on factors such as interface design, responsiveness, and the perceived personalization of advice (Lee and Shin, 2018; Belanche et al., 2019; Martins et al., 2021). Satisfaction in the present study appears to reflect both functional outcomes (perceived investment performance) and experiential dimensions (interface usability, clarity of recommendations), suggesting that successful adoption depends on a combination of practical benefits and user-centered design.

Interestingly, ease of use did not significantly predict adoption in our sample, contrasting with classical TAM and UTAUT findings where effort expectancy often influences behavioural intention (Solberg et al., 2022). This may indicate that among tech-savvy users, particularly millennials and Gen Z, basic navigability is assumed, and adoption decisions hinge more critically on trust and perceived value rather than interface complexity. Similar patterns have been observed in recent FinTech studies, where familiarity with digital tools reduces the relative importance of ease of use compared with trust and usefulness (Bhatia et al., 2020; Piotrowski and Orzeszko, 2023).

The survey findings highlight the nuanced role of trust dimensions in adoption. While competence and integrity were rated highly, transparency and algorithmic fairness were perceived slightly lower, suggesting that users may continue to harbor reservations about the opacity of AI decision-making. Literature emphasizes that trust formation is multi-layered, encompassing technological factors (model quality, explainability), firm-specific factors (brand reputation, service recovery), and system-level factors (regulation, certification) (Anagnostopoulos, 2018; Arner et al., 2016; Montealegre-López, 2025). The Rogo AI case illustrates how platform-level transparency measures, such as performance reporting and portfolio rationales, can mitigate these concerns and enhance adoption.

Overall, these results provide several practical insights. First, trust and perceived usefulness remain key determinants of adoption, suggesting that FinTech providers should prioritize algorithmic transparency, security, and clear demonstration of value. Second, satisfaction acts as a conduit between beliefs and behavioural intention, emphasizing the importance of delivering both functional and experiential quality. Third, the non-significance of ease of use underscores that adoption drivers may differ across demographic groups and digital literacy levels, with younger, tech-savvy users placing less emphasis on effort expectancy. These findings extend prior research by capturing contemporary user attitudes in the context of an innovative AI platform (Rogo AI) and by providing empirical support for the continued relevance of trust and satisfaction in the adoption of robo-advisory services (Davenport and Ronanki, 2018; Helms et al., 2022; Isaia and Oggero, 2022).

Finally, this study reveals persistent literature gaps. Despite the growing evidence base, there remains a shortage of longitudinal studies tracking actual usage over time, limited experimental validation in real brokerage contexts, and minimal attention to the interaction between users' objective financial literacy and subjective trust under volatile market conditions (Dwivedi et al., 2021; Buchanan, 2019; FinTech Global, 2025). Addressing these gaps would provide a more robust understanding of how trust, satisfaction, and perceived usefulness jointly influence adoption trajectories in real-world financial AI applications.

Chapter 6 Conclusion

6.1. Summary of Findings

This study investigated the factors influencing the adoption of robo-advisors in consumer finance, with particular attention to trust, user satisfaction, perceived usefulness, and perceived ease of use. The descriptive statistics and regression analysis revealed that trust, satisfaction, and perceived usefulness were significant predictors of adoption intention. Trust was particularly influential, confirming its role as a cornerstone antecedent in technology-mediated financial services, consistent with prior studies. Within trust, competence and data security were rated highest, whereas transparency and algorithmic fairness received slightly lower scores, indicating areas for providers to enhance user confidence.

Perceived usefulness, including improved decision-making and time efficiency, significantly influenced adoption, reflecting the importance of tangible benefits. Interestingly, perceived ease of use did not show a significant effect, possibly due to the tech-savvy profile of the sample, for whom navigability is assumed, confirming observations from prior FinTech studies (Bhatia et al., 2020; Piotrowski and Orzeszko, 2023). Overall, these findings highlight that trust and satisfaction form the primary drivers for adoption, while usefulness reinforces the perceived value of the service. Contextual insights from Rogo AI suggest that transparent reporting, performance explanations, and user-centered design are essential in cultivating trust and satisfaction, thereby encouraging adoption.

6.2. Research Limitations

Although the useful insights were obtained from the research, various limitations have to be considered. To begin with, the present sample size of 113 responding participants can certainly be considered as adequate to conduct the initial exploratory analysis, yet it can be somewhat insufficient when it comes to generalize the results in the wider context of robo-advisor users in general. Second, the study was based on self-reported informations, which can be biased by virtue of social desirability or recall bias. Third, cross-sectional survey type only proxies the user perception of an insane quote at one moment in time suppressing the opportunities to monitor adoption patterns over the course or track changes in satisfaction and trust levels. Fourth, the sample was mostly tech-savvy and focused in younger age groups, and it may underrepresent older users or the ones with low digital literacy that can impact perceived ease of use. Lastly, although the study presented a real-life scenario of the Rogo AI case, the results might not be applied to other robo-advisory services that have divergent service models, user interface, and regulatory frameworks.

6.3. Suggestion For Future Research

The further research is expected to overcome these drawbacks and develop knowledge of robo-advisor adoption. The longitudinal research designs would enable us to follow the changes in real usage patterns, trust, and satisfaction during the period and have better causal conclusions. Experimental or quasi-experimental designs may also be used by researchers to evaluate the consequences on trust and adoption behavior of particular design affordances, transparency mechanisms or rule-based explanations. Generalizability would be increased by increasing the demographic diversity of the sample, such as older adults, low-literacy groups, and geographic and cultural context participants, and uncover the population specific impediments to adoption. Moreover, the addition of absolute scores of financial literacy and digital competence will help make the relationship between the user capabilities, trust, and perceived usefulness understandable. Finally, comparative studies across multiple robo-advisory platforms would provide insights into best practices, competitive advantages, and the role of firm-level strategies in shaping adoption.

In conclusion, this study establishes that trust, satisfaction and perceived usefulness play a key role in influencing the adoption of robo-advisors among the tech-savvy users, whereas perceived ease of use is less significant to the digitally literate groups. The findings help in the literature related to the adoption of the FinTech and as well as to the real world implication of the faster growing adoption of AI in financial services and the related gaps which are open to future research studies which can further elucidate the changing world of robo-advisor services.

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Appendix 1 Questionnaire For The Research

Factors Influencing the Adoption of AI in Consumer Finance

Start of Block:

Q11 A Research About Factors Influencing the Adoption of AI in Consumer Finance Thank you for taking the time to participate in this survey. The purpose of this study is to understand people's perceptions, experiences, and attitudes toward AI-powered robo-advisors in financial management. Your responses will help us assess trust, satisfaction, perceived usefulness, ease of use, and willingness to adopt these technologies.   There are no right or wrong answers so please answer honestly based on your personal views and experiences. Your participation is voluntary, and all responses will remain confidential and will be used solely for academic purposes.   Completing the survey should take approximately 5–7 minutes. Thank you for your valuable input. Do you agree to participate in this survey?

Q12 Do you agree to participate in this survey?

◯ Yes (1)

◯ No (2)

End of Block:

Start of Block: Default Question Block

Please indicate the Please indicate the extent to which you agree with each of the following statements. Scale: 1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree
Section A: Trust in Robo-Advisors

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
I believe AI-powered robo-advisors make decisions that are in my best interest. (1)	o	o	o	o	o
I trust the accuracy of the investment recommendations made by robo-advisors. (2)	o	o	o	o	o
I believe robo-advisors are transparent about how they operate. (3)	o	o	o	o	o
I am confident that my personal financial data is secure with robo-advisors. (4)	o	o	o	o	o
I believe AI algorithms used by robo-advisors are fair and unbiased. (5)	o	o	o	o	o

Q3 Section B: User Satisfaction

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
Using robo-advisors makes managing my investments easier. (1)	o	o	o	o	o
I feel satisfied with the overall experience of using a robo-advisor. (2)	o	o	o	o	o
Robo-advisors provide helpful explanations of their recommendations. (3)	o	o	o	o	o
I feel in control when using robo-advisors to manage finances. (4)	o	o	o	o	o
My expectations were met when using or learning about robo-advisors. (5)	o	o	o	o	o

Q4 Section C: Perceived Usefulness

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
Robo-advisors help me make better financial decisions. (1)	○	○	○	○	○
I find robo-advisors useful for managing my investment portfolio. (2)	○	○	○	○	○
Robo-advisors save me time in financial planning. (3)	○	○	○	○	○
I can rely on robo-advisors to provide timely financial advice. (4)	○	○	○	○	○

Q5 Section D: Perceived Ease of Use

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
Robo-advisors are easy to navigate and operate. (1)	○	○	○	○	○
Learning how to use a robo-advisor is straightforward. (2)	○	○	○	○	○
I do not need technical knowledge to benefit from a robo-advisor. (3)	○	○	○	○	○

Q6 Section E: Willingness to Adopt

	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
Robo-advisors are easy to navigate and operate.I am willing to use a robo-advisor to manage my finances. (1)	○	○	○	○	○
I would consider switching from a human advisor to a robo-advisor. (2)	○	○	○	○	○
I intend to use a robo-advisor within the next 12 months. (3)	○	○	○	○	○
I would recommend robo-advisors to others. (4)	○	○	○	○	○

Q7 What is your age group?

- ○ 18–24 (1)
- ○ 25–34 (2)
- ○ 35–44 (3)
- ○ 45 or older (4)

Q8 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary (3)
- ○ Prefer not to say (4)

Q9 What is your highest level of education completed?

- College diploma / vocational training (2)
- Bachelor's degree (3)
- Master's degree (4)
- Doctorate (PhD) (5)
- Prefer not to say (6)
- College diploma / vocational training (7)
- Bachelor's degree (8)
- Master's degree (9)
- Doctorate (PhD) (10)
- Prefer not to say (11)

Q10 How would you rate your financial literacy?

○ Very low (1)

○ Low (2)

○ Moderate (3)

○ High (4)

○ Very high (5)

End of Block: Default Question Block

Appendix 2 Research Data

trust_1	trust_2	trust_3	trust_4	trust_5	trust_6	satisfaction_1	satisfaction_2	satisfaction_3	satisfaction_4	s
5	3	4	5	5	5	5	4	5	5	
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