Doctoral School of Economics, Business and Informatics

Thesis Booklet

for the Ph.D. Dissertation by

Sayyed Khawar Abbas

titled

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

Supervisor: Prof. Dr. Kő Andrea
Prof. Dr. Szabó Zoltán

Budapest, 2025

Corvinus University of Budapest

Department of Business Informatics

Thesis Booklet

for the Ph.D. Dissertation by

Sayyed Khawar Abbas

titled

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

Supervisor: Prof. Dr. Kő Andrea
Prof. Dr. Szabó Zoltán

Table of Contents

I. Research Background and Justification of topic selection 4
II. The Methods Used 9
III. Scientific Results of Dissertation 11
A. Results and Discussion (part 1: Qualitative Analysis) 11
B. Results and Discussion (part 2: Systematic Literature Review) 14
C. Results and Discussion (part 3: Quantitative Analysis)..15
D. Conclusion...19
E. Future Research Directions and Limitations...21
IV. Main References...23
V. List of Own Publications on the topic...24

I. Research Background and Justification of Topic Selection

The integration of robotics and artificial intelligence (AI) is fundamentally transforming multiple sectors, from manufacturing and retail to services. As automation advances at an estimated rate of 20% annually, it is anticipated that nearly half of current occupations could be displaced over the next two decades (Acemoglu & Restrepo, 2020; Belanche et al., 2019a; Huang & Lee, 2022a). Among the industries undergoing rapid technological evolution, the financial sector has embraced financial technology (Fintech) as a cornerstone of modern banking and entrepreneurial strategies (Elia et al., 2023). Fintech now extends beyond the basic realms of consumer e-banking and digitalization, aiming instead to craft innovative, customer-centric financial solutions. In this landscape, AI-powered tools offer the potential to redefine value creation for both clients and institutions, accelerating the financial sector's digital transformation (Park et al., 2016).

One of the most notable Fintech innovations is the emergence of Robo-advisors—algorithm-driven, automated platforms that provide personalized investment management services with minimal human intervention. Leveraging AI, machine learning (ML), and big data analytics, Robo-advisors assess clients' financial profiles to curate tailored investment portfolios, making wealth management more accessible and affordable for a wider demographic (Brenner & Meyll, 2020; Hong et al., 2023; Sabir et al., 2023). Financial institutions have increasingly adopted these technologies as strategic tools for gaining competitive advantage, with assets under management projected to reach US$1.78 trillion in 2022 (Statista, 2022; Waliszewski & Warchlewska, 2020). Nevertheless, despite their growing popularity, many consumers remain reluctant to entrust financial decision-making to AI, citing concerns over trust, security, and privacy (Brüggen et al., 2024; Gallo et al., 2024).

Existing research on Robo-advisors largely overlooks the critical perspective of end-users (Arnone, 2024; Huang & Lee, 2022b), focusing instead on technological capabilities and market performance. However, understanding consumer attitudes and motivations is crucial to drive broader adoption. The limited body of work emphasizes the importance of improving usability, with calls for comprehensive models that account for utilitarian and social motivations, demographic factors such as age, culture, gender, and previous familiarity with robot-based systems. Moreover, it is necessary to investigate how these factors interact and moderate user acceptance of

Robo-advisory services.

Parallel to the evolution of Robo-advisors is the rise of conversational AI platforms integrated into everyday services. Instant messaging applications such as Facebook Messenger, WhatsApp, and Slack now allow users to interact with AI assistants for diverse needs (Guise, 2024). In finance, firms like PayPal, Robinhood, and major banks like JPMorgan Chase have adopted AI-based virtual financial assistants—"finbots"—that support users throughout their financial journeys (Cit et al., 2025). Voice-based AI assistants like Siri, Alexa, and Google Assistant further demonstrate the progression toward more intuitive, speech-driven user experiences (McTear et al., 2016; Suhaili et al., 2021).

Despite these advancements, challenges persist. AI assistants often struggle with open-ended or complex user queries and fail to consistently deliver seamless conversational experiences (Marikyan et al., 2022; Liang et al., 2024). Many customers still prefer human interaction over AI-mediated communication, underscoring the need for a deeper understanding of what makes interactions with AI assistants pleasant and effective. In response to these gaps, this research investigates the critical factors influencing customer attitudes toward, and future use of, AI-based Fintech assistants, particularly Robo-advisors. It explores issues of trust, security, and privacy, and examines how utilitarian, social, and demographic factors shape user perceptions and behavioral intentions. By developing and validating new measurement scales, this study contributes to the application of consumer behavior theories in the emerging field of AI-assisted Fintech services.

Ultimately, the findings will offer valuable insights for developers, financial service providers, and policymakers seeking to enhance customer experiences and boost the acceptance of AI-driven financial advisory platforms. In doing so, this research will help bridge critical knowledge gaps and inform strategies for the successful integration of Robo-advisors into the broader financial services landscape. Artificial Intelligence (AI) has revolutionized numerous sectors, fundamentally transforming the way businesses operate and interact with customers (Ritala et al., 2023; Wang et al., 2022). Within the financial services industry, one of the most impactful applications of AI has been the development of Robo-advisors—automated platforms that offer investment management and financial advice using sophisticated algorithms and big data analytics (Lund et al., 2023). Originally created to handle repetitive customer service inquiries, Robo-advisors have evolved into powerful tools that can simulate complex financial advisory services with minimal human intervention (Xie et al., 2023). AI-powered Robo-advisors offer a myriad of advantages. Chief among these is the ability to reduce operational costs significantly (Fotheringham & Wiles, 2022; Zheng et al., 2023). By automating routine customer queries, they alleviate pressure on human agents, operating around the clock and enhancing customer satisfaction through instant support. Furthermore, Robo-advisors collect and analyze vast amounts of consumer data, enabling businesses to deliver personalized services that strengthen customer loyalty and optimize marketing and product strategies (Nirala et al., 2022).

However, the deployment of Robo-advisors also introduces substantial challenges. Developing AI systems capable of managing nuanced customer interactions demands significant investments in expertise and resources (Chow et al., 2023). Additionally, ensuring the reliability and accuracy of Robo-advisors is critical; incorrect or irrelevant responses can damage brand reputation and erode customer trust (Hsu & Lin, 2023). Another major concern is data privacy and security. Since Robo-advisors often handle sensitive financial data, strict compliance with privacy regulations such as GDPR and CCPA is essential (Kooli, 2023).

In recent years, the capabilities of Robo-advisors have expanded alongside advancements in Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLMs). These technologies have enabled Robo-advisors to engage users through more natural, context-sensitive conversations (Pramod Kumar et al., 2021). The evolution of these tools—from simple menu-based bots to advanced AI-powered contextual advisors—has significantly enhanced customer service quality across industries, including banking, real estate, healthcare, and e-commerce (Ahmad et al., 2024).

Various types of Robo-advisors have emerged, including button-based, keyword recognition-based, and contextual bots, each varying in complexity and application (Gupta et al., 2020; Kandpal et al., 2020). Contextual Robo-advisors, utilizing AI and ML, are particularly significant for financial services, given their ability to understand user emotions, predict needs, and offer personalized advice based on historical data patterns.

Nonetheless, the widespread adoption of Robo-advisors faces barriers. User trust remains a central concern, with privacy, security, and brand reputation playing pivotal roles (Chen et al., 2023; Yen & Chiang, 2021). Ethical issues surrounding data usage, algorithmic bias, and transparency in AI interactions further complicate user acceptance (Crawford & Paglen, 2021; Farag et al., 2024). Additionally, companies must balance automation efficiency with potential societal ramifications, such as job displacement and reduced human-centered service culture (Patel & Indurkhya, 2025).

Despite these challenges, the future of Robo-advisors appears promising. As AI technologies become more sophisticated—with advancements in sentiment analysis, predictive analytics, and multilingual support—Robo-advisors are poised to offer increasingly personalized, efficient, and secure services. However, to realize this potential, businesses must prioritize ethical considerations, maintain data privacy and security, and design AI systems that foster trust and user satisfaction. Understanding the adoption and continued use of AI-based Robo-advisors requires grounding in established information systems and technology adoption theories. Several theoretical models inform the conceptual foundation of this study, particularly the Technology Acceptance Model (TAM), the Information System (IS) Success Model, and the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2).

The Technology Acceptance Model (TAM) (Davis, 1989) posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption. While TAM provides valuable insights, it has limitations in capturing the full complexity of user behavior, especially in contexts involving intelligent systems like AI assistants. Recent studies emphasize the need to incorporate additional factors such as trust, hedonic motivation, and anthropomorphism to better explain user behavior in human-AI interactions (Blut et al., 2021; Bhattacherjee et al., 2008).

The Information System (IS) Success Model (DeLone & McLean, 2003) expands the analysis by highlighting information quality, system quality, and service quality as key predictors of user satisfaction and usage intentions. User satisfaction, in turn, influences future technology use. While highly relevant to understanding user evaluations of AI assistants, the IS Success Model alone cannot fully explain behavioral intentions without considering user-centric factors such as privacy concerns, trust, and emotional engagement.

The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012) offers a comprehensive framework by integrating constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. UTAUT2 has proven particularly effective in explaining technology adoption in consumer settings, including mobile payments, online banking, and service robots. However, for Robo-advisors in the financial sector, modifications are necessary to account for constructs like perceived privacy, security, perceived intelligence, and trust, which are critical determinants of adoption.

Given the unique nature of Robo-advisors in Fintech, where financial complexity, regulatory scrutiny, and user risk perceptions are heightened, this study proposes an integrated framework. By combining TAM, IS Success Model, and UTAUT2, and enriching them with constructs such as trust, data privacy concerns, perceived security, and personalization, this research aims to capture the multifaceted dynamics influencing user satisfaction and adoption intentions toward AI-based Robo-advisors.

This comprehensive theoretical foundation not only strengthens the explanatory power of the proposed research model but also addresses important gaps in existing literature, paving the way for a deeper understanding of how AI Fintech solutions can successfully engage and retain customers in an increasingly digital financial landscape.

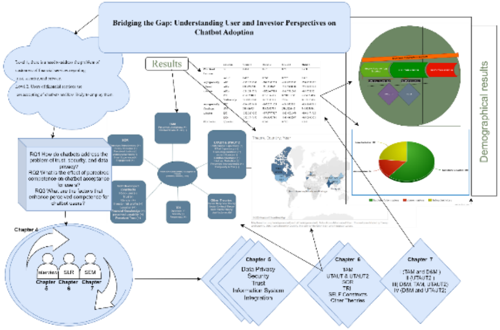

Figure 1: Research Framework (source: Author)

II. The Methods Used

This research employs a mixed-methods approach, combining qualitative and quantitative methodologies to comprehensively examine factors influencing the acceptance and adoption of Robo-advisors in the financial services sector. This approach aligns with the objectives, which require both an in-depth exploration of user perceptions and empirical testing of theoretical models.

.

- Research Approach and Design: Given the multifaceted nature of the research questions concerning user perceptions of trust, security, privacy, and perceived competence, a pragmatic philosophical stance underpins this research. A sequential exploratory design was implemented, starting with qualitative semi-structured interviews and followed by a quantitative survey phase.
- Qualitative Phase (semi structured interviews): Semi-structured interviews were chosen to explore prevailing ethical considerations, behavioral beliefs, and industry-specific insights from fintech managers and employees directly involved with Robo-advisors. The qualitative method facilitates flexible exploration of predetermined and emergent topics, enabling in-depth discussions on trust, security, and data privacy. Interviews were conducted either face-to-face or via video conferencing platforms based on participant convenience, using purposive and convenience sampling techniques. All interviews were recorded (with permission), transcribed, and subsequently analyzed with NVivo software to systematically identify themes.

  Social Representations Theory (SRT) guided this phase, chosen for its ability to address collective understandings of new technologies. SRT effectively captures collective cognitions regarding novel phenomena, making it ideal for examining managers' shared understandings of Robo-advisor technology in financial services.

  Also, section B of this phase conducted in Hungary qualitative interviews conducted using Technology acceptance model as a base framework.
- Quantitative Phase (Structural Equation Modelling (SEM)) : Building upon the qualitative findings, the quantitative phase involved the development and empirical testing of theoretical models derived from the Technology Acceptance Model (TAM) and the DeLone and McLean (D&M) Information Systems Success Model. Structural Equation Modelling (SEM) was employed for hypothesis testing and model validation, leveraging its capability to simultaneously assess multiple

latent variable relationships, including both direct and indirect effects. Quantitative data were collected using a structured questionnaire distributed online through purposive and snowball sampling techniques, targeting Robo-advisors users/investors. The questionnaire was based on validated scales for constructs such as Perceived Trust, Perceived Risk, Perceived Information Quality, Perceived System Quality, Perceived Service Quality, Customer Experience, Perceived Ease of Use, Perceived Usefulness, Attitude Towards Technology, and Intention to Adopt. SmartPLS, Adanco, and R statistical tools were employed for data analysis, validation, and hypothesis testing.

- Sampling and Data Collection: The research included two target populations: fintech managers/employees for qualitative insights and Robo-advisors users/investors for quantitative analysis. Interviews involved fintech professionals from Pakistan and Hungary selected through purposive and convenience sampling. For the quantitative survey, a broader demographic of investors and users of Robo-advisors was targeted using purposive and snowball sampling, aiming for a sample size between 200 and 400, consistent with SEM requirements.
- Data Analysis Techniques: Qualitative data from interviews were analyzed through thematic analysis using NVivo, identifying recurring themes relevant to trust, security, privacy, and competence perceptions. Quantitative data were subjected to SEM analysis using SmartPLS, Adanco, and R software, enabling robust statistical validation of proposed theoretical relationships and the determination of significant predictors of Robo-advisor acceptance. Participants provided informed consent, and confidentiality was strictly maintained throughout. Clear information sheets and consent forms outlined study aims and usage of data. Potential biases due to incentives or participation rewards were controlled through careful monitoring and clear communication of the research objectives. In summary, this mixed-methods approach effectively integrates qualitative depth with quantitative rigor, ensuring comprehensive exploration and validation of factors impacting Robo-advisor adoption in the fintech context.

Table 1. Research Methodology

Section	**Description**	**Tools & Techniques**
Research Design	The research employs a mixed-methods approach combining qualitative and quantitative methods. A sequential exploratory design was used, beginning with qualitative semi-structured interviews	Mixed-methods, Sequential Exploratory Design

Data Collection	Data collection involved semi-structured qualitative interviews with fintech managers and staff followed by online surveys using structured questionnaires distributed among Robo-advisors users and investors.	Semi-structured Interviews, Online Questionnaire
Data Analysis	Qualitative data from interviews was analyzed using thematic analysis with NVivo software and Quantitative survey data were analyzed using Structural Equation Modeling (SEM)	NVivo, SmartPLS, Adanco, R, SEM, Cluster Analysis
Model Development	SEM was used to construct and empirically test a comprehensive model integrating the Technology Acceptance Model (TAM), DeLone & McLean Information Systems Success Model, and UTAUT2 frameworks.	SEM (SmartPLS, Adanco, R), Model Validation
Results and Discussion	Results were analyzed in terms of the accuracy and explanatory power of the SEM model, focusing on significant variables influencing user acceptance of Robo-advisors.	Data Analysis and Interpretation
Conclusion and Future Research	The study concluded that trust, security, privacy, and perceived competence significantly influence Robo-advisors acceptance. Apply the developed model to different fintech scenarios to enhance generalizability.	Planning for future studies, Recommendations

III. Scientific Results of Dissertation

A. Results and Discussion (part 1: Qualitative Analysis)

The findings of the qualitative analysis are presented in three main sections: (1) Robo-advisors in Fintech: Key Challenges and Solutions, (2) Grounded Theory Analysis in Pakistan, and (3) Thematic Analysis in Hungary.

Key Challenges and Solutions

The study identified core challenges and corresponding solutions in adopting Robo-advisors within Fintech contexts, focusing primarily on data security, privacy, trust, and system integration. Experts underlined significant anxieties around cybersecurity breaches, unauthorized data use, and low institutional trust in algorithm-driven systems.

Data Security: Respondents emphasized the critical need for robust data protection, particularly safeguarding financial and personal data from evolving cyber threats. Multi-layered security protocols, regular security audits, and continuous monitoring systems were proposed as essential preventive measures.

Data Privacy: Challenges revolved around uncertainty over data usage and rapidly changing privacy regulations. Recommended solutions included end-to-end encryption, real-time monitoring of conversations, granular GDPR-compliant consent mechanisms, and regular policy updates.

Trust: Gaining user trust in digital-only financial services was notably challenging, especially in markets with lower digital literacy. Educational programs, transparency of operations, visible certification (e.g., ISO 27001), and clear communication about security features were identified as effective trust-enhancement strategies.

System Integration: The integration of Robo-advisors with existing financial systems posed significant operational challenges. Recommendations highlighted collaboration between Fintech companies and traditional banks, ongoing technological innovation, and the use of scalable cloud infrastructure.

Grounded Theory Analysis & SRT theory (Pakistan Context)

Utilizing Grounded Theory methodology on 34 interviews from Pakistani Fintech professionals, this section highlights the nuanced local challenges impacting Robo-advisor adoption.

Emergent Themes: Through iterative open, axial, and selective coding processes, the study derived four main themes: data security, privacy, trust, and information system integration. Respondents consistently emphasized cybersecurity vulnerabilities, evolving privacy concerns, user trust deficits, and system compatibility as primary hurdles.

Data Security: Regular security audits, layered security protocols, and identity verification strategies were crucial solutions proposed to combat cyber threats, reflecting heightened anxiety about the vulnerability of financial data.

Privacy and Trust: Interviewees advocated for advanced encryption, transparency, real-time data monitoring, educational initiatives, and explicit consent processes to address user discomfort and mistrust towards digital financial platforms.

Information System Integration: Respondents underlined the need for collaborative technological frameworks, agile software development, and

responsive design practices to integrate Robo-advisors effectively within existing financial systems, ensuring user-friendly, scalable services.
These findings collectively illustrate the necessity of addressing both technological and socio-cultural barriers, particularly through rigorous security measures and localized user education initiatives.

Thematic Analysis (Hungarian Context)

From 15 expert interviews conducted in Hungary, thematic analysis via NVivo revealed similar yet contextually distinct barriers and solutions to Robo-advisors' adoption:
Data Security Concerns: Hungarian experts strongly underscored cybersecurity threats such as data breaches and hacking. Their recommended countermeasures included rigorous multi-layered encryption, biometric authentication, PSD2 compliance, and proactive threat management systems.
Privacy Management: Respondents expressed significant concerns about the handling of personal data amidst rapidly changing GDPR regulations. Recommended strategies included explicit consent flows, granular privacy dashboards, continuous regulatory compliance monitoring, and clear transparency about data usage.
Institutional Trust and User Literacy: A notable preference for institutional credibility emerged, indicating a lower trust level for digital-only platforms compared to established banks. Solutions involved strategic partnerships between Fintech startups and trusted financial institutions, visible regulatory oversight (e.g., MNB licenses), and broad-based literacy and awareness campaigns to educate users, particularly rural and older demographics.
System Integration and Scalability: Integration with legacy banking systems and ensuring robust scalability were critical issues identified by experts. Proposed solutions included cloud-based autoscaling, microservice architectures, dedicated development teams, and continuous investment in backend R&D.
These insights highlight the intertwined roles of technological robustness, regulatory oversight, user literacy, and institutional credibility in facilitating Robo-advisor adoption in the Hungarian market.

The study conclusively highlights that Robo-advisors' widespread adoption hinges significantly on resolving issues related to data security, privacy, and institutional trust. These findings are consistent across distinct national contexts (Pakistan and Hungary), demonstrating a universal requirement for robust cybersecurity, transparent privacy management, and strategic user education. Solutions consistently emphasized the necessity of multilayered security measures, user-centric educational programs, visible regulatory oversight, and strategic institutional partnerships to enhance trust and acceptance. Future research avenues should address longitudinal analyses, cross-cultural studies, and further empirical validation of these qualitative findings.

B. Results and Discussion (part 2: Systematic Literature Review)

This systematic literature review explored determinants influencing Robo-advisor acceptance within Fintech, synthesizing findings from 22 selected empirical studies.

Determinants of Robo-advisor Adoption

The review identified several theoretical frameworks prominently applied:
Technology Acceptance Model (TAM): TAM emerged frequently, underscoring Perceived Usefulness and Perceived Ease of Use as consistent predictors influencing user intention and behavior towards Robo-advisors across diverse geographic regions including the USA, UK, Portugal, India, China, Spain, and Taiwan.
Unified Theory of Acceptance and Use of Technology (UTAUT): Studies employing UTAUT revealed key determinants such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions significantly impact behavioral intention, particularly in Spain, Taiwan, and China. Further extended models (UTAUT2) introduced variables such as Hedonic Motivation and Perceived Innovativeness, highlighting additional complexity in user acceptance.
Stimulus-Organism-Response (SOR) Framework: Research applying SOR illustrated that Robo-advisors' anthropomorphic features and perceived animacy positively affect user emotional responses and subsequent adoption intentions. However, perceived intrusiveness and privacy concerns were also found as significant inhibitors.
Technology Readiness Index (TRI): Studies using TRI emphasized that user optimism positively influences Robo-advisor adoption, whereas insecurity serves as a barrier, reflecting the critical balance between perceived benefits

and potential risks.

Other Theoretical Approaches: Various other models, such as Social Cognitive Theory (SCT), Diffusion of Innovation (DOI), and Trust Transfer Theory (TTT), contributed insights into psychological and social dynamics influencing user acceptance, including social interactivity, trust, and emotional arousal.

Geographical Insights

Research spanned diverse geographic contexts, including the USA, Germany, China, India, Malaysia, Taiwan, and Spain, indicating the global relevance of Robo-advisor adoption determinants. Cross-cultural variations were noted, suggesting regional differences significantly shape users' perceptions and acceptance behaviors.

Theoretical and Practical Implications

Findings consistently highlighted trust, ease of use, social influence, privacy concerns, and perceived risk as critical determinants influencing Robo-advisor acceptance. This synthesis offers a robust conceptual framework beneficial for academics aiming to further explore Fintech adoption nuances and practitioners seeking strategies to enhance user acceptance and engagement with Robo-advisor technologies.

Future Research Directions

The review identified gaps such as limited differentiation between behavioral intention and actual usage, and exclusive reliance on Scopus and Web of Science databases. Future studies should expand data sources and explore longitudinal or comparative analyses across varying regulatory, cultural, and economic contexts to enrich understanding of Robo-advisor acceptance dynamics.

C. Results and Discussion (part 3: Quantitative Analysis)

This section consolidates the empirical findings from four sequentially developed Structural Equation Models (SEM) that were applied to investigate the acceptance and behavioral adoption of Robo-advisors in the FinTech sector, particularly in the context of Pakistani consumers. The models draw from leading theoretical frameworks—namely the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the DeLone and McLean Information

Systems Success Model (D&M)—and aim to provide a comprehensive understanding of the multifaceted factors shaping user behavior toward Robo-advisors.

Core Determinants of Adoption Behavior

Across all models, Behavioral Intention (BI) consistently emerged as the strongest predictor of Use Behavior (USE), reinforcing the widely accepted postulate in technology acceptance literature that intention is the most proximal antecedent to actual use. Model 4, which integrates TAM, UTAUT2, and D&M with minimal theoretical overlap, demonstrated the highest explanatory power ($R^2 = 0.771$) and predictive relevance (Q^2predict = 0.762), confirming the robustness of this integrative approach.

Key antecedents to BI and USE include:

Performance Expectancy (PE): Found to have a significant positive impact on both BI and USE across all models. Users who perceive Robo-advisors as beneficial to their financial decision-making are more inclined to adopt and rely on them.

Effort Expectancy (EE): Significantly associated with BI and indirectly with USE. This underscores the importance of intuitive, user-friendly design in building adoption intention among FinTech users.

Facilitating Conditions (FC): Strongly related to both BI and USE, confirming that users are more likely to engage with Robo-advisors when they perceive that sufficient technical and informational support is available.

Perceived Information Quality (PIQ) and Perceived Risk (PR): These factors were particularly relevant in enhancing Customer Experience (CE), which in turn affected Intention to Adopt (ITA). Interestingly, PIQ showed a positive relationship with CE, but CE had a nonlinear relationship with ITA, initially reducing intention before enhancing it once a familiarity threshold was crossed.

Unexpected and Complex Findings

Notably, several findings deviated from conventional expectations:

Hedonic Motivation (HM) exhibited a negative influence on BI and USE in all models. This suggests that FinTech users do not seek enjoyment or entertainment in their interactions with Robo-advisors. Instead, they prioritize functional and utilitarian outcomes, perhaps due to the high-stakes nature of financial decision-making where trust and accuracy are more valued than enjoyment.

Habit (HA) was shown to positively influence BI but negatively impact USE. This paradox reveals a possible cognitive dissonance: while users may express willingness to adopt Robo-advisors based on past habits or exposure to similar technologies, they may fail to translate this intention into consistent usage due to entrenched routines, fear of automation, or lack of trust.

Social Influence (SI), contrary to many UTAUT2-based studies, had a negative effect on both BI and USE. This suggests that in the Pakistani cultural context, decisions regarding the use of financial automation are deeply personal and potentially resistant to social persuasion. It also hints at a possible stigma or skepticism toward AI-based financial tools, especially in traditionalist circles.

Perceived Trust (PT) and Perceived Usefulness (PU), though commonly critical in FinTech adoption, demonstrated mixed effects. For instance, PU was negatively associated with ATT in some models, which may reflect latent user concerns around data security, algorithmic opacity, or overreliance on automated financial advice.

Non-Linear Dynamics in User Perceptions

A major contribution of this research is the identification of non-linear (quadratic) relationships between key constructs:

The relationship between Customer Experience (CE) and Intention to Adopt (ITA) displayed a U-shaped curve. At low levels of CE, user skepticism may grow, leading to reduced adoption. However, as CE improves and surpasses a critical threshold, ITA increases sharply, indicating a tipping point in user trust and acceptance.

Similarly, Attitude Toward Technology (ATT) followed an inverted U-shaped curve with ITA, indicating diminishing returns beyond a certain point. Excessive positive attitude, if unsupported by utility or outcomes, may not translate into adoption, possibly due to inflated expectations that go unmet.

These insights underscore the need for strategic calibration of user experiences and attitude-building interventions, focusing on threshold levels at which intention begins to translate into behavior.

Comparative Model Performance and Theoretical Relevance
Among the four models:

Model 1 (TAM + D&M) served as a useful baseline but suffered from limited explanatory ($R^2 = 0.484$) and predictive power ($Q^2 = -0.003$), suggesting it fails to capture the complexity of modern FinTech interactions.

Model 2 (UTAUT2) provided strong statistical performance but lacked theoretical synergy when isolated.

Model 3 combined TAM and UTAUT but introduced conceptual overlap between constructs like PE and PU, slightly weakening theoretical parsimony.

Model 4, integrating TAM, UTAUT2, and D&M, emerged as the most comprehensive and theoretically balanced model, outperforming others across all fit indices (AIC, BIC, HQ, SRMR) and maintaining high discriminant and convergent validity.

Demographic Influences on Adoption

Demographic subgroup analysis revealed nuanced insights:

Education: Users with bachelor's or master's degrees were more sensitive to variables such as PIQ, PE, and PU, underscoring the role of financial and technological literacy in FinTech engagement.

Experience: More experienced users (2–6 years) showed stronger relationships with variables like HA, PE, FC, and PV. Interestingly, less experienced users (under 2 years) exhibited no significant associations, indicating the necessity of sustained exposure to drive meaningful engagement.

Gender: Both male and female users were influenced by PE and SI, but males showed broader variable sensitivity, possibly due to greater exposure to financial tools.

Marital Status: Married users had stronger positive associations with PE, EE, FC, and HA but showed negative sensitivity to SI, indicating a strong self-reliant decision-making approach.

Savings Behavior: Higher savers (30%+ of income) were significantly driven by PE, while lower savers (below 10%) responded more to social cues and habit—revealing segmentation opportunities for FinTech firms.

Implications for Theory and Practice

From a theoretical standpoint, this study provides robust empirical validation for the integration of TAM, UTAUT2, and D&M, while highlighting the contextual relevance of constructs such as CE, PR, and PT in emerging FinTech markets. The findings contribute to expanding technology acceptance theory by demonstrating how cognitive, social, emotional, and experiential factors interact in complex, often non-linear ways.

Practically, the results underscore that effective Robo-advisor design must prioritize trust-building, performance clarity, and ease-of-use. User education, transparent algorithms, and responsive customer support are essential. Moreover, demographic tailoring—such as addressing novice users' needs or customizing interfaces for women or low-saving individuals—could greatly enhance adoption.

D. Conclusion

This study provides a comprehensive evaluation of the factors that influence the acceptance, usage, and perceived competence of Robo-advisors and chatbots in the FinTech industry, particularly within the emerging market context of Pakistan. By leveraging four progressively sophisticated Structural Equation Models (SEMs), this research elucidates the nuanced behavioral, cognitive, and contextual determinants that shape users' intentions and actual usage behavior.

The initial application of the Technology Acceptance Model (TAM) and the DeLone and McLean (D&M) ***Model (Model 1)*** served as a foundational framework but was shown to be insufficient when addressing the complex dynamics of intelligent, human-like systems such as Robo-advisors. While TAM's traditional constructs like Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were statistically relevant, the limited explanatory and predictive power ($R^2 = 0.484$) suggested the need for broader models capable of integrating emotional, social, and habitual elements of user behavior.

Model 2, based on UTAUT2, significantly improved explanatory capacity by introducing constructs such as Habit (HA) and Hedonic Motivation (HM). These additions highlighted the behavioral and affective drivers of adoption, revealing that user intentions are not solely based on rational evaluations of system performance, but also on affective and experiential factors. However, the paradox of hedonic motivation—being positively related to intention but negatively associated with actual usage—points to the gap between initial interest and long-term engagement. This paradox underscores the difference between user excitement and sustained behavioral integration.

To build a more holistic understanding, ***Model 3*** integrated TAM, UTAUT2, and the D&M model, offering a tri-theoretical lens on adoption behavior. It demonstrated that system and information quality—rooted in the D&M model—play a critical role in shaping customer experience (CE), which in turn influences intention to adopt (ITA). This model also emphasized the centrality of Behavioral Intention (BI) as a strong mediator between perceptions and usage, affirming findings in both classic and contemporary technology acceptance literature.

Model 4, the most robust and theoretically streamlined model, excluded overlapping TAM constructs and focused on UTAUT2 and D&M components. With the highest R^2 and predictive accuracy, Model 4 illustrated that user adoption of Robo-advisors is best understood through a multidimensional approach. It emphasized not only technological aspects (performance, effort, system quality) but also behavioral readiness (habit, hedonic aversion), support structures (facilitating conditions), and external pressures (social influence). Importantly, the data showed that social influence had a consistent negative impact on both intention and use, suggesting cultural resistance or skepticism towards automation in financial services—a finding particularly relevant for emerging economies with strong collectivist norms.

Across all models, Behavioral Intention (BI) remained the strongest and most consistent predictor of actual Use (USE), reaffirming the importance of intention as a proxy for adoption behavior. Meanwhile, constructs like Effort Expectancy (EE), Performance Expectancy (PE), Facilitating Conditions (FC), and Perceived Information Quality (PIQ) proved consistently influential across different models. These findings indicate that users are more likely to adopt Robo-advisors when they perceive them as easy to use, effective, well-supported, and intelligent.

However, the analysis also reveals key psychological and social barriers. While habitual behavior positively influences intention, it was found to negatively affect actual use—suggesting that users may conceptually accept the innovation but fail to integrate it into routine behavior. Similarly, the negative role of social influence implies that normative pressures may inhibit the adoption of AI-driven tools, especially when users perceive a divergence from established social or professional norms.

In conclusion, this research advances the understanding of digital financial advisory adoption by presenting empirical evidence that user engagement with Robo-advisors is driven by a constellation of factors: technological readiness, personal behavioral tendencies, cognitive evaluations, and socio-cultural dynamics. Effective adoption strategies must therefore be multifaceted—addressing not only the technical usability of the systems but also the emotional, cultural, and experiential factors that govern human-technology interactions.

E. Future Research Directions and Limitations

The findings from this study open several valuable avenues for future exploration:

Longitudinal Engagement and Hedonic Motivation

One of the most compelling findings—the paradoxical role of hedonic motivation—warrants further investigation. Future studies should consider longitudinal research designs to observe how initial enjoyment translates into (or fails to translate into) sustained use over time. Understanding this trajectory can inform design strategies that convert novelty into habitual usage.

Change Management and Social Norms

Given the adverse role of social influence, future work should explore change management approaches to shift cultural perceptions about Robo-advisors. This includes understanding how social trust, peer education, and institutional endorsement can facilitate acceptance in collectivist societies.

Personalization and Cognitive Adaptability

Developing personalized Robo-advisor experiences based on individual user profiles, financial literacy, and behavioral patterns could enhance user satisfaction and intention. Integration of AI-driven learning and adaptability can also improve the system’s responsiveness and perceived intelligence, further boosting acceptance.

Cross-Cultural Comparisons

Since cultural factors significantly shape technology adoption, cross-national studies can reveal how user behavior toward Robo-advisors varies across economies and sociotechnical environments. Comparative analysis could yield tailored strategies for global FinTech expansion.

Addressing Unmeasured Variables

Despite the models' strength, unobserved variables like technological anxiety, data privacy concerns, or digital literacy might further explain user hesitation. Future studies should enrich the models by incorporating such latent constructs.

Methodological Enhancements

The current study's reliance on self-reported, cross-sectional data presents a limitation in establishing causality. Future research should utilize mixed-method approaches, including experimental designs, in-depth interviews, and real-time behavioral analytics to triangulate findings and strengthen validity.

In summary, this research contributes a theoretically rich and empirically validated framework for understanding Robo-advisor acceptance in FinTech. By embracing an interdisciplinary, user-centric approach, future studies can build on these insights to foster more intelligent, accessible, and trusted digital financial ecosystems.

IV. Main References

Davis, F. (1989). A technology acceptance model for empirically testing new end-user information systems: theory and results. Massachusetts Institute of Technology (1986). MIS quarterly.

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results Massachusetts Institute of Technology].

Davis, F. D. (1987). User acceptance of information systems: the technology acceptance model (TAM).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly, 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. Management science, 35(8), 982-1003.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. Journal of management information systems, 19(4), 9-30.

Venkatesh, A., Kruse, E., & Shih, E. C.-F. (2003). The networked home: an analysis of current developments and future trends. Cognition, Technology & Work, 5, 23-32.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS quarterly, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS quarterly, 157-178.

V. List of Own Publications on the Topic

Abbas, S. K. (2024). AI Meets Finance: The Rise of AI-Powered Robo-Advisors. *Journal of Electrical Systems*, *20*(11), 1011-1016.

Abbas, S. K., Kő, A., & Szabó, Z. (2023). B2B Financial Sector Behavior Concerning Cognitive Chatbots. Personalized Contextual Chatbots in Financial Sector. 2023 14th IEEE International

Abbas, S. K., Kő, A., & Szabó, Z. (2022). Shopping using mobile applications and the role of the technology acceptance model. Hungarian Statistical Review: Journal of the Hungarian Central Statistical Office, 5(2), 54-81.

Abbas, S. K., Szabó, Z., & Kő, A. (2022). Current trends of development in chatbot systems. Specialusis Ugdymas, 1(43), 1157-1168.

Sayyed, K. A., Kő, A., & Szabó, Z. (2022). How Can Business Agility be Addressed with Artificial Intelligence? In OGIK'2022 (pp. 29–30).

Sayyed, K. A., Kő, A., & Szabó, Z. (2021). Why should Chatbots be like Humans? In Aniko Kelemen-Erdos. XVI. FIKUSZ 2021 International Conference : Abstract Book. (2021) ISBN:9789634492719 (pp. 24–24).