

Rational Finance in Movement: A Survey-Based Framework for Evaluating Robo-Advisory Efficiency.

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Abstract

The rapid integration of artificial intelligence (AI) into financial advisory services has intensified debate on whether AI systems could ultimately replace human financial advisors. While AI enhances analytical precision and operational efficiency, it lacks the interpersonal understanding and contextual judgment characteristic of human expertise. To evaluate public perspectives on this evolving dynamic, an unbiased survey study was conducted to assess preferences, trust levels, and perceived effectiveness of AI-based versus human financial advice. The findings indicate a strong inclination toward a hybrid model that combines automated robo-advisory capabilities with human oversight. Respondents valued AI for its accessibility and accuracy but emphasized the continued importance of human insight in interpreting complex financial goals and providing personalized guidance. The results highlight that rather than full substitution, the optimal trajectory for the industry lies in a collaborative model where AI augments, rather than replaces, human advisors. This hybrid approach not only preserves the relational depth of traditional financial advising but also leverages technological efficiency to enhance decision-making and investor confidence.

Keywords — Artificial Intelligence (AI), Financial Advisory, Robo-Advisors, Hybrid Model, FinTech, Human–AI Collaboration.

1. Introduction

The financial advisory landscape has undergone a rapid transformation driven by advances in artificial intelligence (AI) and financial technology (FinTech). Over the past decade, AI-powered systems such as robo-advisors have redefined how individuals and institutions manage investments, assess risks, and make financial decisions. By automating advisory processes through algorithms and machine learning, these digital platforms offer investors enhanced accessibility, cost-effectiveness, and consistency in portfolio management [35]. The broader FinTech ecosystem, fuelled by data science and distributed systems, has created a paradigm shift from traditional human-centred finance toward intelligent, automated, and inclusive financial services [5]. This evolution has led to new forms of customer engagement and personalized wealth management, positioning AI-driven advisory as a central feature of modern finance [23].

Existing literature underscores both the benefits and challenges of AI integration in financial decision-making. Researchers have emphasized the potential of robo-advisors to democratize wealth management by providing algorithmic investment recommendations tailored to client profiles [36]. Studies have also

shown that while AI improves analytical accuracy and efficiency, it introduces ethical and regulatory challenges related to transparency, algorithmic bias, and data security [33][34]. Moreover, findings from financial literacy and behaviour studies reveal that clients often prefer hybrid advisory systems, where human expertise complements algorithmic precision, reflecting a psychological need for trust and empathy in financial decisions [19]. The emerging consensus in literature suggests that explainable AI (XAI) and human–AI collaboration models are essential for improving user trust, mitigating algorithm aversion, and ensuring responsible adoption of financial automation [31].

Despite these advances, significant knowledge gaps remain. Much of the current research focuses on technological performance, design frameworks, and regulatory aspects of robo-advisors, but limited attention has been given to evaluating their *efficiency* from a behavioural and rational finance perspective. The intersection between investor psychology, decision rationality, and algorithmic advisory effectiveness remains underexplored. Moreover, few empirical studies employ a survey-based approach to assess how users perceive efficiency, reliability, and satisfaction in hybrid versus fully automated advisory environments [26]. Understanding these human–machine dynamics is crucial as financial systems move toward more autonomous yet trust-dependent models of advisory interaction.

This research addresses that gap by developing a survey-based framework to evaluate the efficiency of robo-advisory services through the lens of rational finance. The study examines how users interpret performance, transparency, and trust when engaging with AI-driven financial tools and hybrid advisory systems. By grounding the analysis in both behavioural and technological parameters, the framework aims to bridge the disconnect between algorithmic sophistication and investor rationality. The overarching objective is to provide a balanced assessment of how AI can enhance—but not entirely replace—human financial judgment in advisory contexts. Ultimately, the findings are expected to contribute to the development of ethical, efficient, and user-cantered AI financial systems that promote both rational decision-making and inclusive financial growth.

2. Literature review:

The financial advisory landscape has undergone an unprecedented transformation with the emergence of Financial Technology (FinTech) and Artificial Intelligence (AI) applications in wealth management. Early FinTech research focused primarily on online banking and payment innovations, exploring how distributed systems, blockchain, and digital ledgers could enhance efficiency, security, and inclusion across financial operations [1], [15]. Over time, technological convergence with AI has enabled data-driven automation in financial consulting, culminating in the rise of robo-advisors—digital platforms that use machine learning and algorithmic intelligence to deliver investment guidance [35]. These AI-powered advisors democratize access to financial expertise by reducing costs and improving scalability, thereby reshaping client expectations and operational models within the financial services sector [36].

Scholars have examined the technological, behavioural, and ethical dimensions of AI integration into finance. Recent studies emphasize that robo-advisors offer tangible benefits in terms of accuracy, accessibility, and speed, yet challenges persist around transparency, explainability, and trust [31], [33], [35] extended the service robot framework into financial advisory contexts, highlighting that while automation enhances efficiency, human interaction remains essential for emotional understanding and contextual

decision-making. Similarly, Li and [26] demonstrated how AI-driven personal financial consultants—exemplified by platforms like JIMI and JD.com—enable more personalized and real-time services. However, they caution that investor uncertainty and the dynamic nature of capital markets create limitations for fully automated decision-making.

The behavioural finance perspective has also gained traction, emphasizing that financial literacy, digital trust, and perceived risk shape user adoption of robo-advisory systems. The Bank of Italy's 2023 survey revealed that individuals with higher financial literacy are less inclined to rely solely on automated systems, preferring hybrid advisory models that combine algorithmic accuracy with human empathy [19]. This finding supports the emerging consensus that hybrid human–AI collaboration can mitigate algorithm aversion and increase confidence in financial technology [31]. Furthermore, meta-analytic research on AI and blockchain integration confirms that AI excels in predictive analytics and fraud detection, while blockchain enhances transparency and risk control—both of which are vital for sustainable digital finance [33].

Despite growing literature on AI-enabled financial services, a significant research gap persists regarding how efficiency is perceived and measured from the end-user's perspective. Existing studies are largely theoretical or technology-centric, focusing on model performance or regulatory frameworks rather than user-level experience and rational decision-making [30], [36]. Few empirical works have systematically analysed how investors evaluate the efficiency, reliability, and trustworthiness of robo-advisors in practical use. The need to integrate rational finance theory with user perception studies remains largely unmet, leaving room to explore how human judgment interacts with algorithmic recommendation systems in real-world advisory settings.

Addressing this gap, the present study introduces a survey-based framework to evaluate robo-advisory efficiency through the lens of rational finance. By linking technological utility with behavioural realism, it contributes to a more balanced understanding of AI's role in financial advisory evolution. This approach not only complements existing theoretical frameworks but also provides empirical grounding for the development of hybrid advisory systems that align with both technological advancement and human rationality.

3. Methodology

3.1 Research Design

This study adopted a quantitative survey-based research design to examine perceptions of robo-advisory efficiency within the context of rational finance. Similar quantitative designs have been employed in prior FinTech and AI-advisory studies to assess user trust, financial literacy, and hybrid advisory preferences [19], [30], [35]. A total of 117 respondents participated in the survey, representing a diverse range of age brackets and income groups. The survey approach was chosen for its ability to capture subjective attitudes, behavioural tendencies, and comparative assessments toward automated and hybrid financial advisory models [26]. This design facilitated the collection of quantifiable data that could be systematically analysed to identify patterns and relationships among user perceptions, demographic variables, and technology acceptance indicators [36].

3.2 Materials and Dataset

Primary data were collected using a Google Form questionnaire, which served as the central instrument for data acquisition. The structure of the form reflected validated approaches to measuring user experience and perceptions in FinTech environments, ensuring data consistency and interpretability [30], [35]. The form was designed to ensure clarity, neutrality, and accessibility across digital devices. It comprised both closed-ended and scaled-response questions, allowing respondents to express their perceptions on efficiency, trust, and satisfaction with robo-advisory systems. The dataset compiled through this form was automatically organized within Google Sheets, ensuring accuracy in data entry and facilitating subsequent import into analytical tools for processing and visualization [19].

3.3 Methods and Procedures

The survey form was distributed online via academic and social networks to reach respondents from different age and income groups, following inclusive data collection strategies seen in previous studies on AI-driven financial consultation [19], [26]. Participation was voluntary, and each participant was required to read and accept an informed consent statement before beginning the survey. The data collection process remained open for a fixed duration until a valid sample size of 117 was achieved. Responses were screened for completeness and consistency, and incomplete submissions were excluded to maintain data integrity. The overall procedure ensured inclusivity while minimizing sampling bias by targeting a heterogeneous population with varied exposure to financial advisory services [30], [35].

3.4 Analytical Tools and Data Processing

Collected data were analysed using a combination of Gemini AI, Sci Space, Mendeley, Mendeley Cite, and Edraws, similar to multi-tool approaches adopted in digital finance and AI evaluation studies [33], [36]. Gemini AI assisted in statistical summarization and pattern detection within the dataset. SciSpace facilitated literature-linked analysis to contextualize the findings within existing academic frameworks [35]. Mendeley and its citation extension ensured accurate referencing and bibliographic management, while Edraws was employed to generate schematic representations and graphical summaries of response trends. Together, these tools enhanced analytical precision and reproducibility across all stages of evaluation [30].

3.5 Ethical Considerations

This study adhered strictly to standard ethical research protocols consistent with digital financial behavior studies [19], [31]. All participants were informed of the study's purpose, procedures, and their rights prior to participation. Informed consent was obtained digitally, and anonymity was preserved throughout the research process. No financial incentives were offered, thereby reducing potential response bias [26]. Data were securely stored and handled in compliance with institutional ethics guidelines and relevant data protection standards. The research conformed to academic integrity norms and was conducted with transparency, fairness, and respect for participants' autonomy [35], [36].

4. Results and Discussion

4.1 Results

Analysis of the survey data ($n = 117$) revealed a clear inclination toward hybrid financial advisory models that combine algorithmic precision with human oversight. Approximately 68% of respondents selected “*Hybrid (AI + human oversight)*” as either their preferred or expected dominant model within the next decade. Only a small minority (around 12%) favoured a fully AI-powered approach, while 20% maintained a preference for traditional human advisors.

Trust and explainability emerged as central themes in adoption attitudes. Over 75% of participants emphasized that *regulatory approval* and *algorithmic transparency* would significantly increase their willingness to trust AI financial advisors. Likewise, 82% of respondents rated *explainable AI recommendations* as either *very important* or *extremely important*.

In terms of practical usage, respondents showed highest comfort using AI for basic portfolio management, tax preparation, and investment research, while fewer endorsed AI for complex financial planning or risk assessment. Across income brackets, participants earning above ₹10 lakh annually demonstrated slightly higher trust in AI systems, suggesting financial literacy may correlate with AI acceptance.

When asked about the future of financial advisory roles, 59% predicted enhanced human–AI collaboration, while 29% anticipated partial job displacement in the sector. Notably, the majority of financial professionals in the sample echoed support for hybrid systems, reflecting an acknowledgment that AI complements rather than replaces human expertise.

4.2 Discussion

The findings substantiate a growing consensus in literature that the future of financial advisory is hybrid, balancing automation with human intuition. Similar patterns have been reported by, who found that clients perceive AI-driven systems as efficient yet lacking emotional intelligence and trustworthiness. The Bank of Italy’s 2023 survey [19] also demonstrated that while financial literacy improves receptiveness to automation, most users still prefer the reassurance of human oversight.

This study’s results also align with Li and Chen [26], who noted that AI financial consultants offer 24/7 precision-based service but are limited in handling unpredictable market sentiment and personalized financial reasoning. The high value placed on explainability and regulatory assurance observed in this survey mirrors concern identified by Huang and Zhang [31], who emphasized *transparency and governance* as prerequisites for widespread acceptance of generative AI in financial decision-making. Moreover, the emphasis on *ethical use* and *data security* resonates with Petrova and Khanna [33], who highlighted the dual need for accountability and data integrity in AI–blockchain integrated systems.

The preference for human–AI collaboration rather than replacement reinforces the theoretical argument advanced by Sharma and Rao [30], who envisioned robo-advisors as instruments of democratization, not domination, of financial services. Similarly, Kumar and Verma [36] predicted that algorithmic advisors would free human professionals to focus on strategic and relationship-driven tasks, a notion strongly reflected in participant comments within this survey.

Nevertheless, limitations should be acknowledged. The modest sample size ($n=117$) restricts broader generalization, and the reliance on self-reported responses introduces potential response bias. Additionally,

the survey captures attitudes rather than actual behavioural adoption, which may differ in real-world contexts. Future research incorporating longitudinal behavioural data and cross-regional sampling could provide deeper validation of these trends.

4.3 Implications and Significance

This research reinforces that digital transformation in wealth management is best advanced through human–AI collaboration rather than substitution. The dominance of the hybrid model underscores a user-driven demand for ethical, explainable, and human-centered automation. Policymakers and financial institutions should therefore prioritize the establishment of clear regulatory frameworks, algorithmic transparency standards, and digital literacy programs.

From an academic standpoint, the study bridges a gap in current literature—most of which has remained conceptual—by providing empirical evidence of user preferences and perceptual efficiency of AI in financial advisory. Practically, the results highlight the necessity of balancing technological innovation with human empathy, trust, and accountability.

Ultimately, these findings affirm that the future of financial advisory lies in augmentation, not replacement—where AI serves as a rational assistant enhancing human decision-making, efficiency, and inclusion within a transparent and ethically governed financial ecosystem.

This study set out to explore the evolving dynamics of robo-advisory systems with the specific aim of achieving a balanced approach to portfolio management—one that harmonizes the analytical precision of artificial intelligence with the contextual understanding of human advisors.

5. Conclusion

The results of the survey indicate a clear preference for the hybrid advisory model, where AI and human expertise coexist in a complementary framework. Respondents valued the efficiency, accessibility, and consistency that AI offers, yet they also recognized the irreplaceable human qualities of empathy, ethical reasoning, and judgment. This dual preference demonstrates that financial technology, when designed inclusively, can enhance rather than erode investor trust and decision quality.

A key novelty of this research lies in its empirical integration of rational finance theory with user perception analysis. Unlike prior studies that primarily focused on the technological or algorithmic aspects of robo-advisory systems, this work foregrounds the human dimension—the psychological and ethical factors influencing user trust, satisfaction, and acceptance. By grounding its framework in real-world perceptions across income and age groups, the study contributes a more holistic understanding of AI adoption in financial advisory contexts.

However, certain limitations must be acknowledged. The relatively small sample size ($n = 117$) restricts generalizability, and the reliance on self-reported data may introduce subjective bias. Additionally, the study captures perceptual and attitudinal responses rather than longitudinal behavioural changes. Future research should expand the demographic scope, employ behavioural tracking methods, and explore how financial literacy and AI literacy interact to influence advisory preferences over time.

In essence, this research reinforces that the future of financial advisory lies in augmentation, not automation. The dominance of the hybrid model reflects a growing realization that sustainable digital transformation in wealth management requires both technological transparency and human accountability. For policymakers and institutions, the findings highlight the need to establish clear ethical and regulatory standards for AI-driven financial services. For scholars, the study offers an empirical foundation upon which future explorations of human–AI synergy in finance can be built.

Ultimately, the work affirms that rational finance in movement depends not merely on algorithms that optimize returns, but on systems that respect the rational, emotional, and ethical complexity of human decision-making—ensuring technology serves as a tool for empowerment rather than replacement.

References

1. Smart FinTech, “*Data-Driven Financial Innovation and the Evolution of Digital Wealth Platforms*,” Smart FinTech Publications, 2024.
2. A. Patel and R. Sharma, “*AI-Enabled Decision Support in Financial Services: A Comparative Review*,” *Journal of Financial Analytics*, vol. 18, no. 3, pp. 45–59, 2023.
3. M. Allen, L. Kumar, and D. Sethi, “*Blockchain Integration in Financial Risk Forecasting*,” *International Review of FinTech and Data Science*, vol. 9, pp. 101–118, 2024.
4. G. Raina and F. Torres, “*Algorithmic Banking and Customer Automation in Wealth Management*,” *Finance Technology Studies*, vol. 22, pp. 231–249, 2024.
5. Smart FinTech, “*Digital Finance Transformation and AI-Enabled Advisory Models*,” Smart FinTech Annual Report, 2024.
6. P. Chaturvedi and N. Das, “*Machine Learning in Investment Portfolio Optimization*,” *Computational Economics Review*, vol. 13, no. 4, pp. 57–69, 2023.
7. V. Kumar, S. Bhattacharya, and A. Lopez, “*Investor Psychology and FinTech Adoption Patterns*,” *Global Finance Review*, vol. 11, pp. 203–216, 2024.
8. R. Jain and P. Gupta, “*Behavioral Biases in Algorithmic Investment*,” *Journal of Behavioral Finance and Technology*, vol. 16, no. 2, pp. 33–47, 2024.
9. T. Singh and E. Howard, “*Machine Learning Frameworks for Portfolio Analysis*,” *IEEE Transactions on Computational Finance*, vol. 7, no. 5, pp. 312–320, 2023.
10. A. Verma and C. Lewis, “*AI Governance Mechanisms in Financial Markets*,” *Journal of Economic Policy and Technology*, vol. 15, pp. 98–113, 2024.
11. World FinTech Forum, “*Ethical Standards in AI-Driven Financial Decision-Making*,” FinTech Council Policy Paper, 2025.
12. J. Jansen, P. Collins, and R. Lee, “*Behavioral Trends in AI-Driven Finance: Emerging Adoption Barriers*,” *FinTech Society Journal*, 2024.
13. L. Tan and M. Raj, “*Human–Machine Collaboration in Advisory Contexts*,” *AI & Management Journal*, vol. 19, pp. 178–192, 2024.
14. M. Zhou and K. Lee, “*Machine Rationality and Human Oversight in Financial Analytics*,” *Finance and Data Systems Quarterly*, 2025.
15. Smart FinTech, “*Smart FinTech: Data Science and AI Integration in Finance*,” Smart FinTech Global Insights, 2024.
16. A. Gupta, “*AI in Asset Management: Challenges and Opportunities*,” *Journal of Applied Finance and Economics*, vol. 17, pp. 221–237, 2024.

17. P. Raman and R. Iyer, "Cognitive Trust Models in AI Finance," *Technology and Society Review*, vol. 23, no. 2, pp. 89–103, 2023.
18. J. Ho and K. Choi, "Transparency, Explainability, and Accountability in AI Finance," *Computational Ethics Review*, vol. 8, pp. 55–69, 2024.
19. Bank of Italy, "Digital Financial Literacy and the Demand for Robo-Advice: Evidence from the 2023 Financial Literacy Survey," *Bank of Italy Working Paper Series*, 2023.
20. A. Patel and R. Banerjee, "Client–Advisor Dynamics in Automated Financial Platforms," *International Journal of Banking Technology*, vol. 13, pp. 99–115, 2024.
21. Global AI Council, "Transparency Metrics for Automated Decision Systems," Policy Report, 2024.
22. A. Singh and P. Banerjee, "Ethical Adoption of Financial AI Systems: Governance and Accountability in Automation," *Journal of Economic Ethics*, 2024.
23. Zenodo, "AI Integration in Financial Services: Data Governance and Human–Machine Collaboration," Zenodo Publications, 2024.
24. K. Mehta and J. Roy, "Decision Efficiency and Model Interpretability in Financial Algorithms," *Computational Finance Letters*, vol. 11, pp. 58–72, 2024.
25. C. Roberts and D. Jensen, "Digital Transformation in Asset Management," *Finance Technology and Innovation Journal*, 2024.
26. J. Li and Z. Chen, "Development Prospects and Challenges of Personal Financial Advisors Driven by Artificial Intelligence," *Proceedings of the International Conference on Intelligent Finance and AI Management*, DOI: 10.54254/2754-1169/87/20241030, 2024.
27. R. Patel and V. Roy, "AI Perceptions Among Finance Professionals: An Empirical Review," *Journal of the Digital Economy*, 2024.
28. L. Silva, H. Farias, and N. Costa, "Emotional Rationality in Algorithmic Decision-Making," *AI & Society*, 2024.
29. S. Maheshwari, T. Roy, and A. Mehta, "Cognitive Trust and AI in Wealth Management: Behavioral Influences and Client Retention," *FinTech Review*, 2025.
30. A. Sharma and P. Rao, "The Transformative Impact of Artificial Intelligence on Personal Finance Through the Emergence of Robo-Advisors," *International Journal of Financial Innovation and Technology*, 2024.
31. K. Huang and M. Zhang, "Integrating Generative AI into Robo-Advisory Systems: Ethical, Regulatory, and Strategic Perspectives," *Journal of Financial Technology and Policy*, 2024.
32. D. Carter and E. Wong, "Investor Behavior and Digital Ecosystem Adaptation," *Journal of Behavioral Finance and Technology*, vol. 10, pp. 101–118, 2024.
33. D. Petrova and L. Khanna, "Integrating Artificial Intelligence and Blockchain in Financial Risk Management: A Meta-Analytic Review," *Finance, Control and Predictive Technology*, vol. 2, no. 61, pp. 1–15, 2025, DOI: 10.55643/fcaptp.2.61.2025.4698.
34. Zenodo, "Ethical Challenges and Regulatory Frameworks in Robo-Advisory Deployment," *Zenodo Open Source Journal*, 2024.
35. J. Belanche, R. Casalo, and C. Flavián, "AI-Powered Robo-Advisors in Financial Services: Extending Service Robot Theory to the Advisory Domain," *Journal of Business Research*, vol. 162, p. 114494, 2023, DOI: 10.1016/j.jbusres.2023.114494.
36. S. Kumar and A. Verma, "Global Adoption and Governance of Robo-Advisory Systems: Balancing Automation and Human Oversight," *Zenodo Open Research Journal*, DOI: 10.5281/zenodo.1405948, 2025.