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Research paper

Innovation Aversion in Financial Advising: Ambiguity Resolution of Stock Market Investors

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Abstract

Robo-advisors have integrated into financial advisory services, providing consumers with regular investment guidance. Yet, it remains unclear how their visual design affects decision-making in high-risk and uncertain situations, like taking investment advice. This study focuses on preferences and willingness to adopt Robo-Advisors in stock market investments. And, investigated whether the Robo-Advisors are suitable for small investors or investors with less experience in the Stock market. This study investigates the phenomenon of innovation aversion in financial advising, focusing on how stock market investors respond to ambiguity and uncertainty associated with emerging advisory technologies. Through a mixed-method approach combining surveys and in-depth interviews with individual investors, the study reveals that while technological innovation offers potential benefits in terms of efficiency and cost-effectiveness, perceived complexity and lack of personal interaction contribute significantly to innovation aversion. Inferential statistics like one-way ANOVA, Chi-Square , and Regression were used to analyse the adoption and satisfaction of using Robo-Advisors from the data of 119 respondents among residing and Non-residing Indians with the help of IBM SPSS. Thematic analysis was used on qualitative data. The study reveals that the Non-resident Indians have greater satisfaction with these Robo-advisors' platforms. Beginner investors prefer Robo-advisors for their straight-forwardness, while experienced investors tend to be more cautious. Both groups, however, exhibit limited awareness of Robo-advisors, despite the potential benefits they present.

Keywords: *Robo-Advisors; Stock Market Investment; Artificial Intelligence; Trust and Satisfaction.*

1. Introduction

Trust in financial institutions is like the fuel that keeps the engine of the financial system running smoothly. It gives people the confidence to park their money, make investments, and support the flow of capital. Without this trust, the financial system starts to wobble, and the entire economy can slow down. So, when confidence in these institutions is strong, it not only keeps the system stable but also powers growth and innovation across the economy. FinTech uses technology and big data to improve the way we do finance. Kuwait, India, and Singapore are among the top countries where nearly all residents express high confidence in their financial institutions.(Inc, 2024).

Even though people in cities and towns have lost money investing in stocks because they don't know enough about finance. This is because investing often requires personal meetings, which are expensive and only available to the rich.(Sangeetha & S, 2023) The adoption of technology in the financial sector is unfolding effortlessly, with the advent of Robo-advisors emerging as a game-changer in investment strategies, due to their ease of use and efficient portfolio management capabilities. The concept of Robo-Advisors originated in the early 1990s and gained popularity with the rise of online financial services. Although still in its nascent stage within the Indian financial sector, Robo-Advisors have attracted significant attention and show strong growth potential for the future. According to Tracxn data analytics, there are currently 39 fintech companies offering Robo-advisory services in India.("'A Review on the Role of Robo-Advisory Service in Transforming Personal Finance in the Digital- Era,'" 2024)Robo-advisory is an online platform that gathers client details through interactive quizzes, surveys, and forms. It operates under the same regulatory framework as its human counterparts, ensuring compliance with the standards set by the Securities and Exchange Commission. Revenues in the FinTech sector are projected to grow three times faster than those in the traditional banking sector.(Henriques & Sadorsky, 2024) Retail investors engage in trading securities and constructing investment portfolios with the support of financial advisors. They communicate their financial goals and depend on these advisors for guidance, expertise, and assistance in managing various aspects of life planning.(Banerjee, n.d.)

The financial market is complicated, and investors should frequently change their investment plans to get the most out of their money. (Zeng et al., 2024) In September 2022, the global market value was about $104 trillion. Economic growth was expected to drop from 5.7% in 2021 to 4.1% in 2022, but those estimates were too high. Now, global growth has fallen by 2.5%. As a result, predicting stock market trends is one of the most critical economic tasks. Accurate predictions help lower risks for investors and allow them to make smarter investment choices. (Ricchiuti & Sperlí, 2025) Retail investors engage in trading securities, construct investment portfolios with the assistance of financial advisors, and depend on these professionals for financial literacy and life planning skills. In comparison to the rest of the industrialized world, Indians continue to be guided by emotions when it comes to investment. To properly target potential customers, Indian fintech companies must do more rigorous investor profiling based on their investment style, portfolio size, risk appetite, and lifestyle. (Banerjee, n.d.)

The Indian stock market has significantly grown, with its total value reaching a new high of 5 trillion US dollars in May 2024. This growth has been seen across different sectors and has made India the fifth-largest stock market in the world. There are now more than 95 million individual investors in India, who directly own about 10% of the country's publicly traded companies. These investors have invested around ₹36 lakh crore (3.6 trillion rupees) in these companies. They also have invested in equity mutual funds, which have assets worth ₹28 lakh crore (2.8 trillion rupees). Technology has played a crucial role in connecting millions of investors with thousands of companies across India, allowing them to invest and benefit from the growth of these companies. The overall value of all publicly traded companies in India has increased by more than 100 times in the past 30 years.(Echap02.Pdf, n.d.)

Robo advisors work similarly to human financial advisors. They ask customers about their risk tolerance and investment goals before making recommendations. It is estimated that Robo-advisors will manage around 3.13 trillion US dollars worldwide by 2026, which is a significant increase from 2022. Robo-advisors can be cheaper and might offer higher returns than traditional advisors. They are also not influenced by emotions and can avoid behavioural biases.(Wagner, 2024)

A wealth of research has delved into this automated investment advisory system and analysed how Robo-advisors cut down participants' uncertainty by encouraging smart investment decisions, helping investors stay calm and not let emotions affect them, which reduces mistakes that can happen when markets change. Consequently, the pivotal research question that this paper aspires to explore

RQ 1: Do stock market investors prefer Robo-Advisors for investment strategies?

RQ 2: How satisfied are the investors with the adoption of Robo-Advisors?

RQ 3: Are Robo-Advisors suitable for beginners or small investors in stock market investing?

2. Theoretical Background

The financial industry continually seeks advanced methods to forecast market trends and optimize investment decisions. Machine learning (ML) techniques, particularly deep Reinforcement Learning (DRL) and Long Short-Term Memory (LSTM) models, have emerged as powerful tools for enhancing autonomous financial decision-making. DRL, which balances exploration of new strategies with exploitation of existing knowledge, offers key advantages for Robo-advisors, including portfolio scalability and independence from specific market models(Park et al., 2024) By enabling automated yet adaptive investment strategies, DRL can support Robo-advisors in providing personalized recommendations while maintaining consistency and objectivity factors that are crucial for building investor trust. Complimenting this, LSTM-based frameworks excel at capturing sequential dependencies in financial data, making them effective for forecasting stock and cryptocurrency prices.(Ricchiuti & Sperlí, 2025) When integrated into Robo-advisors, LSTM models enhance predictive accuracy and allow for timely, data-driven investment advice, which can improve investors' confidence in automated recommendations. Together, DRL and LSTM approaches demonstrate how combining adaptive learning with robust forecasting can improve both the functionality and reliability of AI-driven financial advisors.

From a theoretical perspective, the technology acceptance and trust framework provides a lens to understand investor adoption of such systems. According to the Technology Acceptance Model(Davis, 1989)Perceived usefulness and ease of use are key determinants of adoption. By improving the accuracy, personalization, and responsiveness of Robo-advisors, DRL and LSTM models can enhance perceived usefulness, which in turn may increase investor willingness to rely on automated investment tools. Similarly, trust in online systems has been shown to influence user engagement.(Harrison McKnight et al., 2002) Suggesting that AI models that demonstrate reliable and transparent decision-making can foster higher investor confidence. Synthesizing these perspectives, the integration of advanced ML models into Robo-advisors not only optimizes financial performance but also plays a critical role in shaping investor trust and adoption.

3. Review of Literature

Artificial Intelligence has revolutionized various financial services, including stock market forecasting. The potential for substantial profits in the stock market has driven both researchers and industry professionals to develop and implement AI-based models aimed at enhancing the accuracy and efficiency of stock performance predictions.(Vanstone & Finnie, 2009)The study proposes an Advisor Neural Network framework utilizing Long Short-Term Memory (LSTM) models to deliver daily investment recommendations by integrating technical indicators, contextual information, and comprehensive financial data. Tested on 417 stocks and 67 cryptocurrencies over three years, the framework achieved superior performance, generating returns of over 41% in the NASDAQ market and 39.38% in cryptocurrency investments, outperforming existing state-of-the-art methods. By enabling Robo-advisors to process complex temporal patterns and adapt to evolving market conditions, LSTM-based algorithms enhance the precision and reliability of investment guidance. This capability supports investor decision-making by reducing uncertainty, increasing confidence, and facilitating more informed, data-driven financial choices. (Ricchiuti & Sperlí, 2025) The rapid growth of the FinTech sector is gaining interest from both individual and institutional investors. This paper explores the return relationship between FinTech stocks and clean energy stocks over time.(Henriques & Sadorsky, 2024)

This study wanted to know why people use Robo-advisors. It found that people are more likely to use them if they think they will be helpful, if they have used them before, and if they trust them. The study also found that people are more likely to use Robo-advisors if they find them easy to use and if they have a habit of using them. This means that Robo-advisors could become more popular in the future.(Sangeetha & S, 2023) Investors' feelings affect how they invest. FACIS is a new investment strategy that considers overreactions and underreactions. The FACIS strategy was compared to other investment strategies using data from China's stock market. It was found to have the best performance, achieving a higher return with less risk.(Zeng et al., 2024)

Robo-advisors are often thought to use complex technology like artificial intelligence, but they use simple algorithms. To improve investment advice, we can either train human advisors better or use more advanced technology in Robo-advisors. Technology experts and financial experts should work together to create better Robo-advisors. It's not clear which approach will be more successful. (Wagner, 2024) Inexperienced investors tend to be motivated by value, while those with more experience are driven by trust. Experienced investors are more likely to find value through effective performance, whereas less experienced ones gain value primarily from educational support. ("Investors' Willingness to Use Robo-Advisors," 2024)

4. Data and Empirical Strategy

This study was conducted by collecting data from stock market investors by using snowball and convenience sampling methods, and the survey was conducted through Google Forms. Survey questions contain both quantitative and qualitative questions. Participants' willingness is ensured by the informed consent attached to the description of the Google form. Forms circulated through social media like LinkedIn, Instagram, and Facebook, etc., by sending to the group created for the stock market investors, and forms circulated by asking for references of known persons who are interested in stock market investment. 119 respondents ensured their responses. Out of which 31 respondents are non-resident Indians. Statistical analysis performed with the help of SPSS for Reliability Statistics, Descriptive statistics for demographic frequency, one-way ANOVA, cross tabulation, Chi-Square, Ordinal Regression, and thematic analysis used to analyse the qualitative data (open-ended question).

5. Data Analysis and Interpretation

Table 1: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
1.000	1.000	3

INFERENCE: The analysis of reliability to assess the consistency of the scaling questions, yielding a Cronbach's Alpha value of 1.000, indicating that the questions are extremely reliable.

Table 2: Demographic Frequency

Items	Details	Frequency	Percent
Gender	Female	56	47.1
	Male	63	52.9
	Total	119	100.0
Age	25 and less than 25	57	47.9
	26 - 35	45	37.8
	36 - 45	12	10.1
	46and above	5	4.2
	Total	119	100.0
Educational Qualification	High School / Intermediate	7	5.9
	Postgraduate	40	33.6
	Professional	23	19.3
	Undergraduate	49	41.2
	Total	119	100.0
Annual Income	2,50,000 - 5,00,000	21	17.6
	5,00,000 - 10,00,000	18	15.1
	Above 10,00,000	13	10.9
	Below 2,50,000	67	56.3
	Total	119	100.0
Residential Status	Non-Resident Indian	31	26.1
	Residing in India	88	73.9
	Total	119	100.0

INFERENCE: The dataset consists of a slightly higher proportion of males (52.9%) compared to females (47.1%), with a predominant age group being 25 years or younger (47.9%), where the age group more than 46 is less in number (4.2%). Most participants have completed undergraduate education (41.2%) or postgraduate education (33.6%). Most respondents (56.3%) earn below 2,50,000 annually, and a significant portion resides in India (73.9%), though a notable number are NRIs, which adds a layer of global diversity to the findings. These characteristics indicate that the sample is primarily young, educated, and from lower-income backgrounds, with a diverse mix of respondents both residing in India and living abroad. These demographic factors are expected to influence the responses and outcomes within the study.

Table 3: Awareness of Existence of Robo-Advisors in Stock Market Investment Using Chi-Square

Item		Residential Status		Total
		Non-Resident Indian	Residing in India	
Awareness of the existence of Robo-Advisors in Stock Market Investment	Maybe	3	13	16
	No	18	47	65
	Yes	10	28	38
Total		31	88	119

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Monte Carlo Sig. (2-sided)		
				Significance	99% Confidence Interval	
					Lower Bound	Upper Bound
Pearson Chi-Square	.535[a]	2	0.765	.804[b]	0.793	0.814
Likelihood Ratio	0.566	2	0.754	.804[b]	0.793	0.814
Fisher's Exact Test	0.457			.804[b]	0.793	0.814
N of Valid Cases	119					

INFERENCE: The relationship between residential status and awareness of the Robo-advising platform was examined using the Pearson Chi-Square test. The analysis yielded a Chi-Square value of 0.535, which is greater than P=0.05. Hence, there is no significant relationship between residential status and the awareness of the Robo-Advising platform. This suggests that awareness of Robo-Advising is consistent across different residential categories, highlighting that geographic locations do not appear to influence with these financial services.

Table 4: Bayesian Estimates of Coefficients for the Satisfaction of Using Robo-Advisors Based on the Residential Status

Parameter	Posterior			95% Credible Interval	
	Mode	Mean	Variance	Lower Bound	Upper Bound
Non-Resident Indian	2.968	2.968	0.03	2.628	3.307
Residing in India	2.807	2.807	0.011	2.605	3.008

INFERENCE: The Bayesian Estimates of coefficients state that the satisfaction level of using Robo-advisors in stock market investments of Non-resident Indians is high (3.307) compared with the investors residing in India (3.008). It reveals that Non-Resident Indians are more satisfied with Robo-Advisors for stock market investments.

Table 5: Chi-Square to Measure the Preferences of Robo-Advisors in the Stock Market

		Number of years of experience in stock market investment				
		1 - 2 years	3 - 4 years	Less than a Year	More than 4 Years	Total
I prefer Robo-Advisors for	Easy to access	5	1	20	1	27
	Easy to access, Others	0	0	1	1	2
	Others	2	0	13	2	17
	Safety / Reliability	3	2	17	0	22
	Safety / Reliability, Easy to access	0	1	3	1	5
	Safety / Reliability, Others	1	0	0	0	1
	Safety / Reliability, To avoid human conflicts, Easy to access	1	0	2	1	4
	To avoid human conflicts	4	2	18	3	27
	To avoid human conflicts, Easy to access	3	0	10	1	14
Total		19	6	84	10	119

INFERENCE: The above table shows that the majority of respondents (84) with the experience of less than a year of investment prefer Robo-Advisors for Easy Access and to avoid human conflicts. And the respondent with more than 4 years of experience shows hesitance to adopt these investment platforms.

Table 6: Chi-Square

Chi-Square Tests						
	Value	df	Asymptotic Significance (2-sided)	Monte Carlo Sig. (2-sided)		
				Significance	99% Confidence Interval	
					Lower Bound	Upper Bound
Pearson Chi-Square	22.485[a]	24	0.55	.519[b]	0.506	0.532
Likelihood Ratio	21.843	24	0.589	.619[b]	0.606	0.631
Fisher's Exact Test	23.326			.446[b]	0.433	0.458
N of Valid Cases	119					

INFERENCE: The chi-square test yielded a significance value of 0.550 ($p > 0.05$), indicating no statistically significant association between investors' years of experience in the stock market and their preference for the Robo-Advisors platform. This suggests that familiarity or tenure in traditional investing does not necessarily dictate adoption of digital advisory services, highlighting that factors other than experience, such as technological readiness or perceived convenience, may play a more critical role in influencing investors' preferences.

Table 7: Ordinal Logistic Regression to Analyse Trust Level of Using Robo-Advisors, Whether Robo-Advisors are Suitable for Beginners, and How Likely Investors Recommend Robo-Advisors to Small Investors

Model Fitting Information				
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	213.657			
Final	185.313	28.344	13	0.008

INFERENCE: The observed data value of the model fit in the ordinal regression shows that the significance value of 0.008, which is less than the P value of 0.05 it indicates that Robo-Advisors are trustworthy and suitable for beginners in the stock market investment, and it is recommended for small investors.

Table 8: Goodness of Fit

	Goodness-of-Fit		
	Chi-Square	df	Sig.
Pearson	167.698	197	0.936
Deviance	147.665	197	0.996

INFERENCE: The above table shows the Pearson significance value of 0.936, which is greater than the P value of 0.05; therefore, the model fits the data well. The selected ordinal regression analysis demonstrates a good fit for the observed data.

Table 9: Pseudo R- Square

	Pseudo R-Square
Cox and Snell	0.212
Nagelkerke	0.232
McFadden	0.098

INFERENCE: The model shows a moderate ability to explain the outcome, with Nagelkerke's R^2 indicating the highest explanatory power at 23.2%. This reflects a reasonable fit; it also implies that there may be other unmeasured factors influencing the outcome.

Table 10: Parameters

Particulars		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	High School / Intermediate	-19.378	1.737	124.475	1	0	-22.782	-15.974
	Postgraduate	-16.794	1.716	95.825	1	0	-20.156	-13.431
	Professional	-15.858	1.715	85.515	1	0	-19.219	-12.497
Location	Satisfaction	0.404	0.22	3.356	1	0.067	-0.028	0.835
	Trust=Agree	1.019	1.233	0.684	1	0.408	-1.396	3.435
	Trust=Disagree	0.236	1.263	0.035	1	0.852	-2.24	2.711
	Trust=Neutral	-0.256	1.154	0.049	1	0.824	-2.519	2.006
	Trust=Strongly Agree	0.148	1.39	0.011	1	0.915	-2.577	2.873
	Trust=Strongly Disagree	0[a]			0			
	Recommend=Definitely	-3.104	1.166	7.094	1	0.008	-5.389	-0.82
	Recommend=Definitely Not	15.462	4676.562	0	1	0.997	-9150.431	9181.356
	Recommend=Not sure	-2.504	1.124	4.962	1	0.026	-4.708	-0.301
	Recommend=Probably	-2.248	1.119	4.037	1	0.045	-4.44	-0.055
	Recommend=Probably Not	0[a]			0			
	Suitable for beginners of the stock market=Agree	-15.923	0.603	697.724	1	0	-17.105	-14.742
	Suitable for beginners of the stock market=Disagree	-15.059	0.766	386.586	1	0	-16.56	-13.558
	Suitable for beginners of the stock market=Neutral	-14.707	0.613	576.125	1	0	-15.908	-13.506
	Suitable for beginners of the stock market=Strongly Agree	-15.441	0		1		-15.441	-15.441
	Suitable for beginners of the stock market=Strongly Disagree	0[a]			0			

INFERENCE: The ordinal logistic regression analysis revealed several significant predictors of the outcome variable. Educational thresholds—High School/Intermediate (Estimate = -19.378, $p < 0.001$), Postgraduate (-16.794, $p < 0.001$), and Professional (-15.858, $p < 0.001$)—were all negatively associated with the dependent variable relative to the reference category, suggesting that higher education levels strongly decrease the likelihood of higher outcome scores.

Among recommendation categories, respondents who answered "Definitely" (Estimate = -3.104, $p = 0.008$), "Not sure" (-2.504, $p = 0.026$), and "Probably" (-2.248, $p = 0.045$) were significantly less likely to report higher outcome levels compared to the reference.

Furthermore, perceptions of suitability for beginners in the stock market were consistently significant: agreement (-15.923, $p < 0.001$), disagreement (-15.059, $p < 0.001$), neutrality (-14.707, $p < 0.001$), and strong agreement (-15.441, $p < 0.001$) all had strong negative associations relative to the reference, indicating that respondents' views on beginner suitability heavily influenced their reported outcome.

In contrast, location satisfaction ($p = 0.067$) and trust-related variables (all $p > 0.4$) were not statistically significant, suggesting that these factors do not meaningfully affect the dependent variable.

Fig. 1: Word Cloud.

Image created with the help of a word cloud based on the question about trust and security concerns of using Robo-advisors in stock market investment.

This word art shows that there are mixed emotions about adopting Robo-advisors in stock market investment because of the trust and security concerns involved. People are more concerned about sharing their personal details when it comes to money. But still, Robo-advisors are familiar with the younger generation because of their easy access and diversification. Trust in digital platforms is closely linked to perceptions of cybersecurity, accountability, and explainability. Research further highlights that users often prefer human advisors when automated systems appear opaque or vulnerable. Thus, data protection, transparency, and user confidence emerge as recurring themes in the literature, underscoring the necessity for advanced solutions that enhance both security assurance and interpretability in Robo-advisory services.(Jency & Anto Kumar, 2025)

6. Thematic Analysis

6.1. Trust issues

People concerned about the algorithms used by Robo-advisors may not always provide accurate advice. The fluctuations in the market trend might also make investors wary of trusting these platforms. A few worried about what happens if the investment fails, and who's responsible. It's important to educate the investors about the benefits they offer as well as how they can be used to meet their investment goals. Robo-advisors must ensure transparency regarding their investment approaches, associated risks, and the fees they impose. Users demonstrate scepticism toward automated financial services, underscoring the necessity of transparent communication, explainable decision-making, and adherence to regulatory standards to build confidence.(Abbas et al., 2025) Confidence in algorithmic accuracy, platform credibility, and robust data security significantly influences investor willingness to adopt automated financial services. Platforms that combine transparent AI recommendations, strong institutional reputation, and secure, user-centric system design are more likely to build investor trust and encourage broader adoption.(Cao et al., 2025) Initial trust in financial robo-advisors among young retail investors varies significantly, influenced by individual factors such as prior experience, financial literacy, and risk tolerance. Trust is strengthened when services demonstrate competence, transparency, and personalized recommendations aligned with investors' goals.(Nourallah, 2023)

6.2. Security and data privacy

Most of the respondents mentioned data breaches, unauthorized access, and hacking risks. Some users worried that personal information might be leaked or misused while using these Robo-Advisors for stock market investments. The absence of technological proficiency among users can be a key obstacle to embracing Robo-advisors. Handling sensitive financial data and personal information further complicates the process. Robo-advisors must establish stringent security frameworks to defend against potential threats, including fraud, data breaches, and other cybersecurity vulnerabilities. The uptake of Robo-advisors critically depends on how investors perceive fairness in decision-making and the protection of their personal data. Data privacy and cybersecurity emerge as critical barriers, necessitating robust protective measures such as encryption, multi-factor authentication, and compliance with best practices. Enhancing the user experience through intuitive interfaces, clear disclosure of data usage, and targeted educational initiatives further mitigates perceived risks. Additionally, collaboration with financial professionals and continuous technological innovation are essential strategies to reinforce trust, strengthen security, and promote broader adoption of FinTech solutions, ultimately supporting financial inclusion in developing economies.(Abbas et al., 2025)

7. Findings and Discussions

Our empirical research has two relevant results: first, related to the classification of the accuracy method, and second is the combination of qualitative and theoretical background. The inferential analysis indicates that the satisfaction levels of non-resident Indians utilizing Robo-advisors are higher compared to those of investors residing in India. Investor preferences for Robo-advisors differ based on their experience levels in stock market investments. Investors with limited stock market experience Favor Robo-advisors for ease and conflict-free investing. Whereas investors with high experience show hesitance to prefer these Robo-advisors. When it comes to awareness, both residing and Non-Residing Indian lacks the information about Robo-Advisors. As a starting point for stock market involvement, Robo-advisors provide a trustworthy and affordable path to stock market participation for even the smallest of investors.

Secondly, the thematic analysis highlights the key concerns like trust, security, and data privacy. While less experienced and younger investors are more receptive to adopting digital platforms like Robo-advisors, key concerns such as trust, security, and data privacy remain. These concerns, particularly regarding the protection of personal information and the risk of cybersecurity breaches, persist despite their willingness to embrace this technology. In the real investment environment, there are not only uncertainties, but also emotional and psychological factors influencing the selection of the investment tools and platforms. The results indicate that perceived ease of use and perceived control both play a significant role in shaping perceived usefulness, which ultimately boosts individuals' willingness to engage with Robo-advisors.

8. Practical Implications

The findings of this study have several implications for practice and policy. First, the higher satisfaction reported by non-resident Indians highlights a growing international market for Robo-advisory services, suggesting that fintech providers should design globally scalable platforms with features tailored to cross-border investors. Second, the openness of novice investors to automated platforms underscores the need to position Robo-advisors as inclusive entry-level tools that can broaden retail participation in financial markets, provided they are supplemented with investor education and literacy initiatives. Third, persistent concerns about trust, security, and data privacy call for greater transparency in algorithmic decision-making and robust cybersecurity frameworks, which are critical for reducing innovation aversion and ensuring responsible adoption. Finally, the hesitance of experienced investors points to the value of hybrid advisory models that combine algorithmic efficiency with human oversight, enabling fintech firms and financial institutions to appeal to diverse investor segments while safeguarding confidence in digital finance.

9. Limitations and Future Studies

To enhance the understanding of this phenomenon, it's essential to incorporate factors like personal financial objectives, market trends, regulatory shifts, and other influential variables. While this study relies on surveys for data collection, future research using qualitative methods such as interviews or focus groups could offer richer insights into the underlying reasons for specific behaviours or perspectives. This study employed snowball and convenience sampling to recruit participants with relevant stock market experience. While these non-probability methods facilitated access to a dispersed population, they may introduce selection bias, limiting the generalizability of findings to the broader population. Future research should employ larger, randomized samples to enhance external validity.

10. Conclusion

In conclusion, machine learning, especially Deep Reinforcement Learning (DRL), has transformed financial trading by enabling efficient, scalable, and automated decision-making. The advent of automated investment advice has transformed the methods and processes involved in providing investment guidance within financial institutions. Evaluating the performance of AI trading robots offers valuable insights into their profitability and potential, highlighting their importance in contemporary financial strategies. The integration of an automated methodology with human judgment, when optimally combined, can yield superior results compared to decisions made independently by either the automated model or the human alone. The research identified performance expectancy, established habits, and trust in Robo-advisors as crucial determinants of investors' willingness to embrace financial Robo-advisors. Additionally, the research highlights the impact of perceived ease of use and perceived control on enhancing the perceived usefulness of Robo-advisors, ultimately influencing users' willingness to engage with these platforms.

References

[1] "A Review on the role of Robo-advisory service in transforming Personal Finance in the Digital Era." (2024). *Journal of Informatics Education and Research*. https://doi.org/10.52783/jier.v4i2.1077.

[2] Abbas, S. K., Szabó, Z., & Kő, A. (2025). Robo-Advisors in Fintech-Challenges and Solutions. *Acta Polytechnica Hungarica*, *22*(6), 131–151. https://doi.org/10.12700/APH.22.6.2025.6.9.

[3] Banerjee, S. (n.d.). Portfolio management with the help of AI: What drives retail Indian investors to robo-advisors? *THE ELECTRONIC JOURNAL OF INFORMATION SYSTEMS IN DEVELOPING COUNTRIES*, *n/a*(n/a), e12346. https://doi.org/10.1002/isd2.12346.

[4] Cao, X., De Zwaan, L., & Wong, V. (2025). Building trust in robo-advisory: Technology, firm-specific and system trust. *Qualitative Research in Financial Markets*. https://doi.org/10.1108/QRFM-02-2024-0033.

[5] Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008.

[6] *Echap02.pdf*. (n.d.). Retrieved October 24, 2024, from https://www.indiabudget.gov.in/economicsurvey/doc/eschapter/echap02.pdf.

[7] Harrison McKnight, D., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *The Journal of Strategic Information Systems*, *11*(3), 297–323. https://doi.org/10.1016/S0963-8687(02)00020-3.

[8] Henriques, I., & Sadorsky, P. (2024). Do clean energy stocks diversify the risk of FinTech stocks? Connectedness and portfolio implications. *Global Finance Journal*, *62*, 101019. https://doi.org/10.1016/j.gfj.2024.101019.

[9] Inc, G. (2024, May 16). *5 Things to Know About the World's Biggest Election*. Gallup.Com. https://news.gallup.com/poll/645041/things-know-world-biggest-election.aspx.

[10] Investors' willingness to use robo-advisors: Extrapolating influencing factors based on the fiduciary duty of investment advisors. (2024). *International Review of Economics & Finance*, *94*, 103411. https://doi.org/10.1016/j.iref.2024.103411.

[11] Jency, I., & Anto Kumar, R. P. (2025). FinQuaXBot: Enhancing trust and security in personalized investment and tax forecasting using homomorphic encryption and meta-reinforcement learning with explainability. *Expert Systems with Applications*, *287*, 128136. https://doi.org/10.1016/j.eswa.2025.128136.

[12] Nourallah, M. (2023). One size does not fit all: Young retail investors' initial trust in financial robo-advisors. *Journal of Business Research*, *156*, 113470. https://doi.org/10.1016/j.jbusres.2022.113470.

[13] Park, J.-H., Kim, J.-H., & Huh, J.-H. (2024). Deep Reinforcement Learning Robots for Algorithmic Trading: Considering Stock Market Conditions and U.S. Interest Rates. *IEEE Access*, *12*, 20705–20725. https://doi.org/10.1109/ACCESS.2024.3361035.

[14] Ricchiuti, F., & Sperlí, G. (2025). An Advisor Neural Network framework using LSTM-based Informative Stock Analysis. *Expert Systems with Applications*, *259*, 125299. https://doi.org/10.1016/j.eswa.2024.125299.

[15] Sangeetha, S., & S, Vignesh. (2023). Perception of Investors on Robo Advisory Services. *2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 1–6. https://doi.org/10.1109/ICAECA56562.2023.10199926.

[16] Vanstone, B., & Finnie, G. (2009). An empirical methodology for developing stockmarket trading systems using artificial neural networks. *Expert Systems with Applications*, *36*(3), 6668–6680. https://doi.org/10.1016/j.eswa.2008.08.019.

[17] Wagner, F. (2024). Determinants of conventional and digital investment advisory decisions: A systematic literature review. *Financial Innovation*, *10*(1), Article 1. https://doi.org/10.1186/s40854-023-00538-7.

[18] Zeng, Z., Xu, W., Peng, Z., & Zhong, Y. (2024). Online Portfolio Selection of Fuzzy Mean Regression Strategy Considering Investor Sentiment Based on Text Data. *International Journal of Computational Intelligence Systems*, *17*(1), 1–11. https://doi.org/10.1007/s44196-024-00611-8.