AI In Personal Financial Planning – Robo Advisors Vs Human Advisors

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ABSTRACT

This study examines the comparative role of robo-advisors and human advisors in personal financial planning by surveying 150 banked retail investors. Using a descriptive–analytical design and convenience sampling, the research explores respondents' demographic profiles, perceived effectiveness, trust, and personalized guidance across advisor types. Results show that human advisors are rated higher on perceived effectiveness trust and personalized guidance on 5-point scales; differences are statistically significant. Respondents nonetheless recognize robo-advisors' strengths in cost-efficiency, accessibility, and automated discipline. The findings indicate that while AI-driven robo platforms have democratized access to financial planning, human advisors retain a comparative advantage where empathy, complex judgment, and relationship-based trust matter most. Given these complementarities, hybrid advisory models that combine algorithmic efficiency with human oversight appear promising. The study's convenience sample limits generalisability; future research should use stratified or probability sampling and longitudinal designs to examine actual portfolio outcomes and adoption dynamics over time. Policymakers and firms should emphasize transparency, algorithm explainability, and client education to raise trust in digital advice while preserving human support where needed.

Keywords:Artificial Intelligence, *human advisors, robo-advisors*

INTRODUCTION

`Artificial Intelligence is a field of computer science that makes robots and algorithms that can do things that require human-like thought, such as learning, thinking, perceiving, and making decisions. The ideas of AI come from formal logic and early computer science (Alan Turing's work in the middle of the 20th century). There were also times when AI was nicknamed "AI winters," and now we live at a time where machine learning and deep learning are the most important things, thanks to advancements in the 2010s. Most modern AI systems used in banking use machine learning, probabilistic models, and sometimes neural networks to make decisions and tailor services to each customer. There are easy-to-read histories and summaries of institutions that cover this vast arc. Personal financial planning has become an important part of modern living since it helps people organise their savings, assets, and wealth. In the past, human financial advisors have been very important in helping customers make decisions about money by giving them personalised advice, using their knowledge, and understanding how money decisions might affect their emotions. But because of how quickly AI and digital technologies are getting better, robo-advisors have changed the way people think about financial planning.

Robo-advisors are digital platforms that use AI to give automated, algorithm-based portfolio management and financial advice with little to no human involvement. They are cheap, easy to find, and can give you investment suggestions based on data. On the other hand, human advisors have a lot of expertise, a full understanding of money management, and the capacity to deal with behavioural and psychological issues that algorithms might miss. The argument between robo-advisors and human advisors has gotten a lot of attention because each have their pros and cons. Robo-advisors are great because they are fast, flexible, and cheap. But human advisors are still better when it comes to things that need empathy, trust, and complicated financial decisions. In many circumstances, hybrid models that combine AI technologies with human experience are becoming a good way to satisfy the needs of a wide range of clients. As technology gets better and financial markets get more active, it's important to understand how AI may help you organise your finances. By comparing robo-advisors and human advisors, we can learn a lot about how people may make smart choices that balance new technology with gut feelings to improve their financial health.

OBJECTIVES OF THE STUDY

- To evaluate whether robo -advisors are as effective as human advisors in delivering personal finance planning outcomes.
- To analyse client preferences between robo-advisors and human advisors, with a focus on trust and personalized guidance.

REVIEW OF LITERATURE

Cardillo, G., & Chiappini, H. (2024). the study states that employs a systematic literature analysis to examine articles on robo-advisors from 2017 to 2022. Our analysis delineates four pertinent research domains: initial categorisation of robo-advisors, behavioural aspects, performance evaluation, and algorithmic modelling. Lastly, we suggest pertinent study questions for each stream, offering researchers novel research perspectives. Our ideas are also useful for banks, asset managers, and other financial organisations because clients' preferences and cost structures change when they use robo-advisors.

Orgeldinger, J. (2024). The study examines robo-advising's pros, cons, and regulations. It stresses how robo-advisory services reduce risk, generate returns, and manage portfolios. They provide individualised investing advice utilising technology and skill, replacing traditional advisors. The article also discusses robo-advisor fees and financial advisor perks. It states that traditional financial advisors charge 1–1.5% of total assets managed, whereas robo-advisors charge 0–0.25% for basic services. The study also discusses how fees affect investment performance and presents index ETF-based robo-advisors to reduce fees. Hybrid and pure robo-advisors are explained further. In addition, the report lists significant robo-advisors and their assets under management. It finds that AI could improve robo-advising by analysing data, making tailored suggestions, and communicating with investors.

Back, C., Morana, S., & Spann, M. (2023). The study states that the Robotic advisers, AI-enabled digital service agents, are advising investors more. We investigate if and why robo-advisors improve investment decisions. We examine the well-known disposition effect, which states that investors are more likely to realise past profits than past losses, in two significant induced-value experiments. We find that robo-advisors minimise investors' impact on disposition Adding social design aspects like a name and natural language communication to the robo-advisor decreases investment behaviour and improves the disposition impact. This effect is mediated by investors seeking guidance less from robo-advisors with social design aspects Our findings also suggest that asking human-like robo-advisors for assistance is more psychologically difficult and that social design, a common technique, may pose hazards.

Shiao, H. T., Pagliaro, C., & Mehta, D. (2022).The study Advised investors may make rash judgements like selling all assets during market turbulence like the COVID-19 epidemic. Financial advisors can help clients avoid such decisions with proactive behavioural coaching. Which clients need the most help? Financial advisors can benefit from a prediction algorithm that identifies clients most likely to react to market volatility. This innovative data source was utilised to train a machine-learning model to identify investors in need of intervention during tumultuous markets. To further understand investment intention, the authors add a unique dataset of investor-initiated contacts (web, email, and phone) and web activity (page view and browsing history) to the model. The authors use this novel dataset, advisor remarks, transaction activity, and a market volatility index to develop a machine-learning algorithm to identify advised investors who need proactive intervention. The authors explain how such work affects traditional and robo-advisory service models.

METHODOLOGY

Research Design

The present study adopts a descriptive and analytical research design. The descriptive design focuses on outlining the demographic and financial characteristics of respondents It helps in presenting a clear picture of the population under study. The analytical design, on the other hand, is employed to evaluate and compare the effectiveness, trust, and personalized guidance offered by robo-advisors and human advisors. This involves the use of statistical tools such as mean, standard deviation, and independent sample t-tests to analyse differences in perceptions and determine the significance of observed variations**.**

Sampling Technique

Convenient sampling refers to the selection of respondents who are readily available and agreeable to participate in the study, thereby facilitating efficient data collection. In this study, a total of 150 customers' were selected based on their accessibility and willingness to participate, ensuring a practical and feasible approach to data collection within the given constraints.

DATA ANALYSIS AND INTERPRETATION

Table-1

Demographic Profile

Variable	**Category**	**No of respondents**	**Percentage**
Age group	18–30 years	35	23
	31–45 years	55	38
	46–60 years	40	26
	60+ years	20	13
	Total	**150**	**100**

Gender	Male	95	63
	Female	55	37
	Total	**150**	**100**
Occupation	Salaried employees	70	47
	Self-employed/business owners	40	27
	Professionals (CA, doctors)	25	16
	Retired	15	10.0
	Total	**150**	**100**
Annual Income	Below 5 lakhs	30	20
	5–10 lakh	65	43
	Above 10 lakhs	55	37
	Total	**150**	**100**
Investing Experience	Less than 2 years (Novice)	40	27
	2–7 years (Intermediate)	70	47
	More than 7 years (Experienced)	40	26
	Total	**150**	**100**
Investment Instruments	Mutual Funds / SIPs	70	46
	Stock Market (Shares/ETFs)	25	17
	Fixed Deposits / Bonds	30	20
	Retirement/Insurance Products	25	17
	Total	**150**	**100**

Source: Primary data

The demographic profile of the 150 respondents reveals that the majority belong to the 31–45years age group with 55 respondents as they are in the early stage of investment where there are having knee interest to investment where with 20 respondents belongs to the age group of 60 years as now their earnings are not much as compared to earlier so they are not much investing. Aged 46–60 years 40 respondents indicating that most participants are in their prime financial decision-making years, The male respondents are 95 where they are mostly in the mind set to invest because they earnings are in that stage where they can easily make investment decision, where 55 respondents are female showing growing female participation in financial planning.

In terms of occupation**, salaried employees 47%** form the largest group, followed by **self-employed/business owners 27%, professionals 16%,** and **retired individuals (10%)**, reflecting a mix of active earners and retirees. Income distribution shows that most respondents fall in the **₹5–10 lakh bracket 43%**, with **37% earning above ₹10 lakh** and**20% below ₹5 lakh**, highlighting their middle-to-upper middle-income status. In terms of investing experience, nearly half **47%** have **2–7 years of experience**, while **27% are beginners** and **26%** are seasoned investors, ensuring diverse perspectives.

Table -2

Showing the Effectiveness of Robo-Advisors vs. Human Advisors

Variables	**N**	**Mean**	**Std. Deviation**
Robo Advisors	60	3.65	0.82
Human Advisors	90	4.05	0.70

Source: primary data

The comparison of mean effectiveness scores indicates that human advisors (M = 4.05, SD = 0.70, n = 90) are rated more effective in delivering personal financial planning outcomes compared to robo-advisors (M = 3.65, SD = 0.82, n = 60). Both groups achieved above-average ratings on the 5-point scale, but the higher mean for human advisors suggests that respondents perceive them as more reliable and effective, likely due to factors such as personalized guidance, trust, and relationship-based advisory services. The higher standard deviation observed in robo-advisors (0.82) compared to human advisors (0.70) further suggests that opinions regarding robo-advisors are more varied, reflecting different levels of familiarity, trust, and acceptance of AI-driven platforms. Overall, the results imply that while robo-advisors are emerging as a viable option, human advisors still maintain a competitive edge in terms of perceived effectiveness.

Table 3

Mean Trust Scores of Robo-Advisors vs. Human Advisors

Advisor Type	N	MeanTrust Score	Std. Deviation	t-value	Df
RoboAdvisors	60	3.40	0.88	-5.64	148
Human Advisors	90	4.20	0.72		

Source: primary data

The analysis of trust levels between robo-advisors and human advisors shows a clear difference in perception among respondents. Human advisors recorded a higher mean trust score (M = 4.20, SD = 0.72) than robo-advisors (M = 3.40, SD = 0.85). The independent samples t-test value ($t = -5.85$, $p < 0.01$) confirms that this difference is statistically significant at the 1% level, indicating that investors place significantly greater trust in human advisors. The higher mean score for human advisors highlights that trust in financial decisions still depends largely on interpersonal relationships, professional credibility, and emotional reassurance—qualities that automated systems cannot fully replicate. On the other hand, the relatively lower mean and higher variation in responses for robo-advisors suggest mixed confidence levels, likely influenced by concerns over data security, algorithm transparency, and limited human oversight. These findings emphasize that while AI-based robo-advisors are gaining acceptance, trust remains a critical barrier to their full adoption, and human advisors continue to hold a strong advantage in establishing reliability and confidence among clients.

Table 4

Mean Personalized Guidance Scores of Robo-Advisors vs. Human Advisors

Advisor Type	N	Mean Guidance Score	Std. Deviation	t-value	Df
Robo-Advisors	60	3.55	0.80	-6.12	148
Human Advisors	90	4.30	0.68		

The analysis of personalized guidance between robo-advisors and human advisors reveals a significant difference in investor perceptions. Human advisors received a higher mean guidance score (M = 4.30, SD = 0.68) compared to robo-advisors (M = 3.55, SD = 0.80). The independent samples t-test value ($t = -6.12$, $p < 0.01$) indicates that this difference is statistically significant at the 1% level. This shows that respondents strongly prefer human advisors when it comes to personalized guidance in financial planning. The higher mean score suggests that investors value the human ability to provide tailored advice, emotional understanding, and adaptability to individual financial goals—factors that AI-driven robo-advisors currently struggle to match. In contrast, the lower mean and higher standard deviation for robo-advisors reflect that perceptions of their guidance vary more widely, possibly due to limited trust, lack of emotional connection, or unfamiliarity with digital advisory tools. Overall, the results highlight that human interaction remains a crucial factor in personal financial planning, particularly in providing customized and empathetic financial advice.

Conclusion

The present study demonstrates that human advisors continue to be perceived as more effective, more trusted, and better at providing personalised guidance than robo-advisors among a sample of banked retail investors. Although robo-advisors deliver clear benefits—lower fees, scalable automation, and disciplined rebalancing—respondents value the interpersonal elements of advice that humans provide: tailored solutions, behavioural coaching, and reassurance during market stress. The greater variability in perceptions of robo-advisors highlights uneven familiarity and lingering concerns about algorithmic transparency and data security. Practically, these results argue against viewing robo and human advice as substitutes; instead, they support hybrid solutions that leverage algorithms for efficiency while reserving human expertise for complex planning and trust-building. For practitioners, enhancing explain ability, providing clear disclosures, and offering optional human touch points can increase digital-advice adoption. For researchers, the study suggests a need for larger, more representative samples and outcome-based (rather than perceptual) measures of advisory effectiveness. In sum, robo-advisors are an important innovation in personal finance but—at present—best deployed as complements to, not replacements for, human advisory capacity.

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