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Impact of AI Driven Financial Advisory Tools on Personal Investment Behaviour in Emerging Market

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Abstract
The rapid emergence of Artificial Intelligence (AI) in the financial services sector has transformed how individuals make investment decisions, particularly in emerging markets like India. This study looks into how retail investors' personal investing habits are affected by AI-driven financial advising tools. The main goal is to investigate the ways in which AI-powered investing platforms impact risk preferences, portfolio selections, and investment decisions. Additionally, the main elements influencing the acceptance and trust of these technologies will be identified. The study uses both primary and secondary data in a mixed-method approach. The young investors between the ages of 20 and 30, who make up the most active and technologically proficient group of retail investors in India, will be given structured questionnaires to complete in order to gather primary data. To investigate the interactions between variables and find the underlying behavioural aspects driving adoption and trust, statistical approaches such factor analysis, structural equation modelling, and analysis of variance (ANOVA) will be used. It is anticipated that the results will shed light on how AI-based advisory tools might improve financial inclusion, encourage wise investment choices, and foster confidence in nascent fintech ecosystems.

Keywords: FinTech, Investment Behaviour, Retail Investors, Emerging markets, and Factors.

Introduction
Artificial Intelligence (AI) has been a disruptive factor in a number of industries, including the financial services industry, in recent years. The emergence of robo-advisors, or AI-driven financial advising systems, has fundamentally altered how ordinary investors make financial choices. These online resources use big data, predictive analytics, and machine learning algorithms to optimise asset allocation plans, automate portfolio management, and provide individualised investing advice. In order to offer individualised investment recommendations, AI-driven financial advisory systems examine enormous information, such as consumer preferences, market movements, and risk profiles. These systems, in contrast to traditional advisors, are able to rebalance assets, monitor portfolios continuously, and modify plans in response to real-time data. A rising number of individual investors are drawn to AI-based platforms because of its efficiency and personalisation, particularly in emerging nations

where there has historically been little access to reasonably priced and objective financial advice.

Background of the Fin Tech Innovations in India

The emergence of fintech innovations in India has changed the way people think about investing. As platforms like Groww, INDmoney, Zerodha, Paytm Money, and Kuvera gain popularity, artificial intelligence (AI) is becoming a vital part of the investing ecosystem. These systems predict market moves, suggest investment portfolios, and assist investors in making data-driven financial decisions through the use of sophisticated algorithms. Young, tech-savvy investors have also adopted these tools more quickly as a result of India's digital revolution, rising smartphone usage, and government programs that support financial inclusion (such the Jan Dhan Yojana and UPI-based services). The significant portion of new retail investors are millennials and Generation Z, especially those in the 20–35 age range. Digital financial literacy, self-directed investing, and a strong propensity for technology adoption define this group. For them, the ease, accessibility, and transparency they desire in personal financial management are provided by AI-driven advising platforms. The combination of behavioural finance and technical innovation presents a unique research opportunity in developing markets such as India. Gaining knowledge on how AI technologies affect risk-taking behaviour, investing attitudes, and decision-making processes might help one better understand how the dynamics of financial involvement are changing. This is particularly true in cities like Chennai, where a sizable number of educated investors and young professionals use digital investing platforms.

Research Problem

Artificial Intelligence (AI) is a major impact on the financial services sector in recent years, especially with the rise of robo-advisors, or AI-driven investment advisory tools. Due to initiatives for financial literacy, smartphone usage, and greater internet penetration, there is a growing interest in digital investing platforms in India, particularly among the younger generation those between the ages of 20 to 35. It is unclear, meanwhile, how much AI-powered advice tools influence their risk tolerance, investment choices, and financial confidence. Additionally, consumers' adoption and dependence on these AI tools may be significantly influenced by elements like perceived accuracy, ease of use, perceived trust, and technological savvy. Examining how retail investors view and engage with AI-driven investment advisors is crucial in the context of Chennai, a developing metropolitan financial centre with a diversified population of young professionals. For fintech start-ups, legislators, and financial institutions looking to increase technology adoption and boost retail investors' financial decision-making, an understanding of these behavioural dynamics might yield important insights.

Review of Literature

The existing body of literature demonstrates that artificial intelligence (AI)-powered robo-advisors are transforming financial advisory services, shifting from human-led advice to automated, data-driven decision systems. Early foundational studies (Sironi, 2016; D'Acunto et al., 2019) describe robo-advisors as algorithmic tools capable of automated portfolio construction, rebalancing, and low-cost investment management. Over time, scholars (Zhu, Vigren & Soderberg, 2024; Anagnostopoulos, 2023) highlight the integration of big data, machine learning, and predictive analytics, which enable personalised advice tailored to user behaviour, preferences, and risk profiles. The emerging from the literature is adoption behaviour and influencing factors. Studies grounded in technology acceptance theories (Tao et al., 2022; Belanche et al., 2019) emphasize that *perceived usefulness, ease of use, trust, and transparency* strongly influence user adoption of robo-advisors. Social design elements—such as human-like interfaces—have mixed effects: Back, Morana, and Spann (2023) find that while robo-advisors reduce certain behavioural biases (e.g., disposition effect), adding overly human features may introduce psychological resistance. There are few studies also examine behavioural and financial outcomes. The study suggests that robo-advisors can improve diversification, reduce emotional trading, and enhance portfolio efficiency (Bhagat et al., 2022; D'Acunto et al., 2019). However, results vary depending on algorithm design, fee structures, and user engagement. The trust and algorithmic transparency remain critical concerns, with users demanding clarity about how recommendations are generated (Ambrosio et al., 2023; Fletcher & Gruber, 2022). The regulatory perspectives increasingly dominate recent discussions. Scholars (Anagnostopoulos, 2023; Zhu et al., 2024) note growing challenges related to algorithmic accountability, fairness, transparency, data privacy, and explainability, urging robust governance models and regulatory frameworks from international context. Now reviewed for the India-focused literature (Jain & Purohit, 2024) highlights rapid adoption of AI-enabled investment tools, particularly among young, technology-friendly investors. While accessibility is high due to mobile-first platforms, concerns over data security, algorithmic opacity, and regulatory uncertainty remain prominent. The study identified of the existing of the review literature shows a clear evolution: from simple rule-based automation to sophisticated, user-centric advisory ecosystems shaped by AI, behavioural science, and UX design.

Research Gap

The fintech adoption and digital investment platforms have been the subject of previous study, little is known about how AI-driven financial advisory tools affect the individual investing habits of retail investors in developing countries. Studies that have already been done mostly concentrate on developed economies and the factors that influence technical adoption, but they ignore behavioural issues like risk tolerance, financial confidence, and trust in AI assistance. Furthermore, little research has been done on the specific regions of India, especially in urban areas like Chennai, where fast digitalisation and demographic diversity may have a special impact on investor attitudes and interactions with AI-based financial advisors.

Research Methodology

The present study following specific objectives are: i) to explore the ways in which AI-powered investment advisory tools influence personal investment behaviour among retail investors in India; ii) to analyse Artificial Intelligence influence adoption and factors for AI advisors in respective study area; and iii) to suggest suitable policy measures for the ensure and regulation of the AI with help of investors in India.

The research design used in this study is exploratory and descriptive. While the descriptive component focusses on examining trends, attitudes, and variables impacting retail investors' adoption and trust of AI-based financial advisory tools, the exploratory component seeks to comprehend the growing role of artificial intelligence (AI) in influencing individual investment behaviour. The study uses a non-probability snowball sampling technique to gather information from Chennai-based retail investors between the ages of 20 and 35. Because young investors using AI-driven financial advise products are not a formally listed or easily recognisable target market, snowball sampling allows the researcher to access respondents by way of recommendations from initial participants. This method works well for exploratory research that seeks to identify behavioural trends rather than draw broad conclusions about the entire population. The study's demographic consists of Chennai-based retail investors between the ages of 20 to 35 who either use or are aware of AI-based financial advising platforms like Groww, INDmoney, Zerodha, Kuvera, and Paytm Money. The study obtains primary data through a structured questionnaire designed to elicit quantitative information from respondents. Data were mostly collected using Google Forms and online survey links, which were distributed via email, WhatsApp groups, LinkedIn, and other investment-related online networks to reach the target market of young retail investors in Chennai. In addition to primary data, the study used secondary data from credible and relevant sources such as academic journals and research publications, industry papers produced by SEBI, NITI Aayog, and PwC, as well as corporate websites and fintech market analysis. These secondary sources contributed to contextual understanding and the interpretation of primary data findings.

Result and Discussion

The Artificial Intelligence increasingly integrates with personal finance and investment activities, understanding how investors perceive, adopt, and utilise AI-enabled advisory platforms becomes crucial for both academic research and policy development. The Artificial Intelligence increasingly integrates with personal finance and investment activities, understanding how investors perceive, adopt, and utilise AI-enabled advisory platforms becomes crucial for both academic research and policy development. This analysis has been systematically addressed for the demographic characteristics of the respondents, their awareness and usage patterns of AI-based investment tools, age-wise variations in trust and perception, and the key factors influencing adoption as identified through statistical techniques such as ANOVA and factor analysis. The results are not only presented through descriptive statistics but are also interpreted in relation to broader behavioural finance theories and technological adoption models. The discussion further connects the empirical observations with emerging trends in fintech adoption among young retail investors, especially in rapidly digitising markets like India. The study also highlights that the how AI-driven financial tools are reshaping traditional investment behaviours, influencing decision-making patterns, and altering the dynamics of trust, risk perception, and financial autonomy among investors. The study findings that the comprehensive interpretation of the data, offering insights into both the behavioural and technological dimensions of AI-based financial advisory systems, ultimately contributing to a deeper understanding of their implications in an emerging market context.

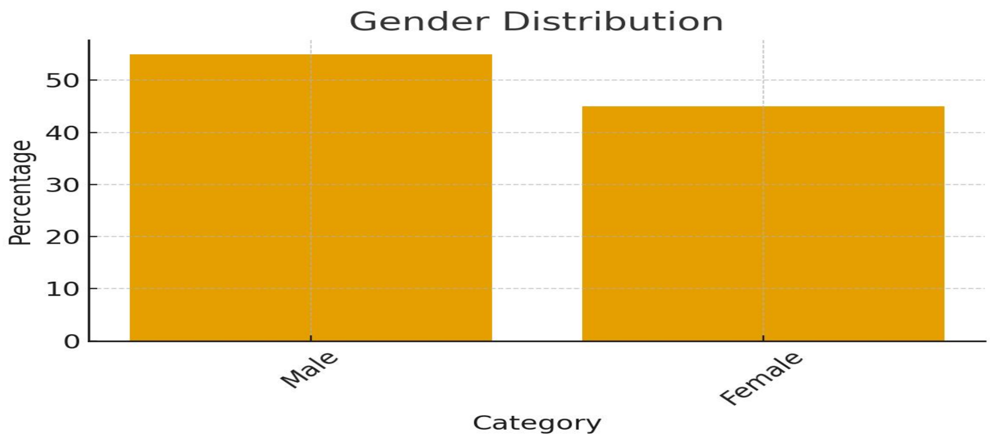
Table: 1 Demographic Profile of Respondents

Category	**Content**	**Respondents (n = 160)**	**Percentage (%)**
Gender	Male	88	55
	Female	72	45
	Total	160	100
Age	20–25 years	64	40
	26–30 years	73	46

	31–35 years	23	14
	Total	160	100
Education	Undergraduates	79	49
	Postgraduates	26	16
	Professional Degree	21	13
	Others	34	21
	Total	160	100
Occupation	Students	46	29
	Private Sector Employees	89	56
	Government Employees	12	7
	Others	13	8
	Total	160	100
Monthly Income (₹)	Below 25,000	39	24
	25,001 – 50,000	55	34
	50,001 – 75,000	26	16
	Above 75,000	40	26
	Total	160	100
Awareness of AI-driven Financial Tools	Yes	154	96
	No	6	4
	Total	160	100
Usage of AI-driven Financial Advisors	Yes	154	96
	No	6	4
	Total	160	100
Platforms Used	Groww AI	63	39
	INDmoney	41	26
	Zerodha	26	17
	Kuvera	19	12
	Paytm Money	11	6
	Total	160	100
Frequency of Use	Daily	83	52
	Weekly	26	16
	Monthly	22	14
	Rarely	29	18
	Total	160	100

Source: Primary Data

The above table 1 presents the demographic characteristics of the retail investors surveyed in Chennai. and took for the total of 160 respondents participate of the study. The gender composition shows that 55% of the respondents were male and 45% were female, indicating a relatively balanced participation. The age-wise, the largest segment (46%) belonged to the 26–30 age group, followed by the 20–25 group (40%), suggesting that AI-driven financial advisory tools are predominantly used by young and tech-savvy investors. The educationally, nearly half of the respondents were undergraduates (49%), while 16% were postgraduates and 13% held professional degrees, indicating a diverse educational background among users of AI financial tools. The occupational data show that 56% were private sector employees, highlighting strong adoption among working professionals, while students accounted for 29% of the sample. The income distribution reveals that 34% earn between ₹25,001 and ₹50,000, and 26% earn above ₹75,000, reflecting that AI-based financial advisory platforms attract individuals with moderate to high disposable income. The among respondents' awareness and usage levels are exceptionally high, with 96% of respondents both aware of and using AI-driven financial advisory tools. The digital platforms of AI used, Groww AI emerged as the most preferred (39%), followed by INDmoney (26%) and Zerodha (17%). The study concluded that the half of the respondents (52%) use AI tools daily, demonstrating strong integration of AI-driven insights in personal investment decision-making. The following flow chart provides a detailed explanation of the key variables used in the analysis, including gender, age, AI usage, and frequency of using AI-based investment



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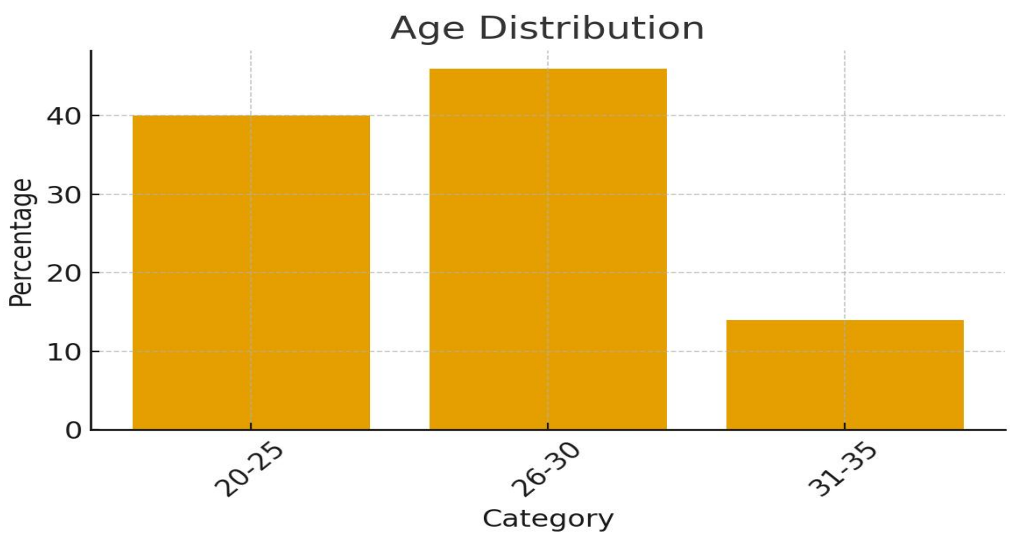

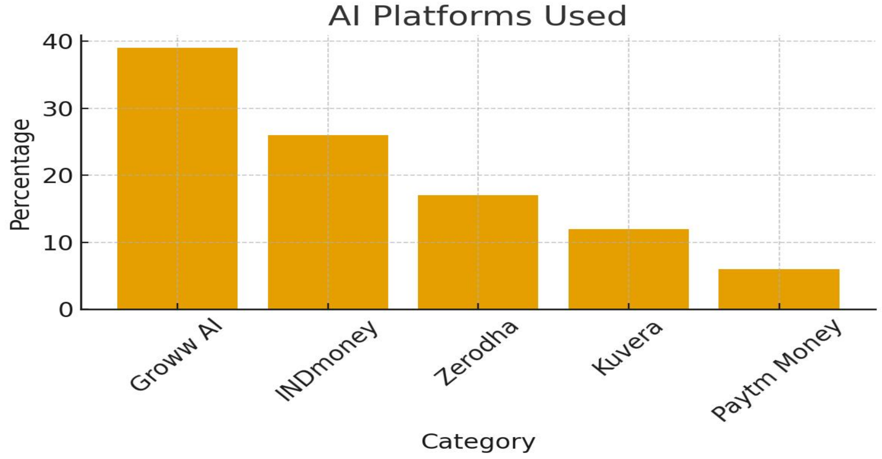

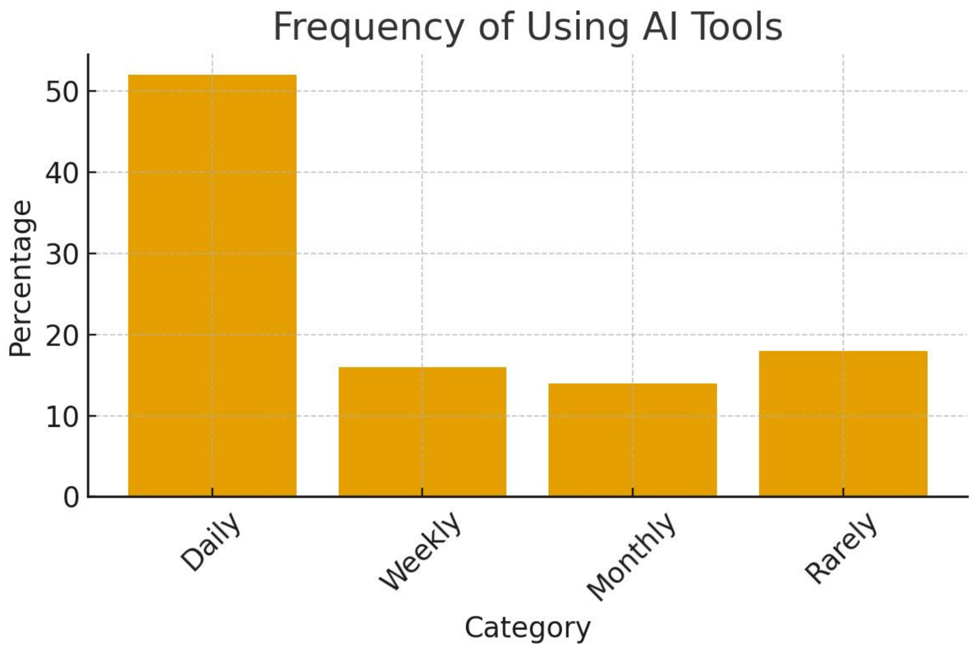

Table 2: Investment Behavioural Patterns of Retail Investors in Chennai

Variables	Categories	Frequency (n=160)	Percentage (%)
Investment Experience	Less than 1 year	34	21.3
	1–3 years	56	35.0
	Above 3 years	70	43.7
Primary Investment Objective	Wealth Creation	78	48.8
	Short-term Gains	36	22.5
	Retirement Planning	28	17.5
	Children's Education	18	11.2

Preferred Investment Avenue	Equity Shares	66	41.3
	Mutual Funds	52	32.5
	Derivatives	12	7.5
	Bonds/Fixed Income	30	18.7

Source: Primary Data.

The above table 2 highlights the behavioural investment patterns of the surveyed retail investors. There is significant portion (43.7%) have more than three years of investment experience, indicating a mature and informed investor base in Chennai. The result shows that the wealth creation emerges as the most common investment objective (48.8%), showing a long-term orientation among respondents. In equity shares remain the most preferred investment avenue (41.3%), followed by mutual funds (32.5%). The study findings that the distribution reflects growing confidence in market-linked instruments and increased financial awareness among retail investors.

Table 3: Factors Influencing Investment Decisions of Retail Investors

Factors	Agree (%)	Neutral (%)	Disagree (%)
Risk Appetite	62.5	18.7	18.8
Market Information & Trends	71.2	15.0	13.8
Financial Literacy Level	66.3	20.0	13.7
Advice from Financial Experts	54.4	23.7	21.9
Social Influence (Friends/Relatives)	47.5	25.0	27.5
Past Investment Experience	69.4	16.3	14.3

Source: Primary Data

The above table 3 outlines the key determinants of retail investors' decision-making. Market information and trends are the strongest influence, with 71.2% agreeing that they rely on current market updates. The study result that the financial literacy also plays a crucial role (66.3%), indicating the importance of awareness and knowledge in investment choices. It also shows that the past experience influences 69.4% of respondents, highlighting the tendency to make decisions based on previous outcomes. The study findings that the interestingly, social influence has a comparatively lower impact (47.5%), suggesting that investors increasingly rely on formal sources of information rather than peer suggestions.

Table 4: Descriptive Statistics of Key Investment Variables

Variables	N	Mean	Standard Deviation (SD)	Minimum	Maximum
Risk Appetite Score	160	3.42	0.88	1.00	5.00

Financial Literacy Score	160	3.67	0.79	1.50	5.00
Market Awareness Score	160	3.81	0.74	2.00	5.00
Investment Performance Score	160	3.55	0.82	1.50	5.00
Decision Confidence Score	160	3.46	0.91	1.00	5.00

Source: Primary Data.

The above table 4 presents the descriptive statistics for key variables influencing investor behaviour. The market awareness score (Mean = 3.81) is the highest among all variables, indicating that retail investors in Chennai actively follow market updates and information. The study result shows that the financial literacy also shows a relatively strong mean value (3.67), suggesting that respondents possess a moderate to high level of understanding of financial concepts. The risk appetite and decision confidence have similar mean scores (3.42 and 3.46), implying that most investors are moderately comfortable with taking risks and making independent investment decisions. The result suggests that the financially informed and market-aware investor population.

Table 5: Correlation Matrix Between Investment Variables

Variables	Risk Appetite	Financial Literacy	Market Awareness	Investment Performance	Decision Confidence
Risk Appetite	1	0.312**	0.285**	0.354**	0.406**
Financial Literacy	0.312**	1	0.421**	0.388**	0.365**
Market Awareness	0.285**	0.421**	1	0.447**	0.392**
Investment Performance	0.354**	0.388**	0.447**	1	0.436**
Decision Confidence	0.406**	0.365**	0.392**	0.436**	1

Note: Correlation is significant at the 0.01 level (2-tailed).

The above table 5 presents the Pearson correlation coefficients among the major investment behaviour variables. The study findings that the all variables show significant positive correlations, indicating that improvements in one behavioural factor tend to enhance the others. The market awareness exhibits the strongest correlation with investment performance (r = 0.447), suggesting that investors who stay updated with market trends experience better investment outcomes. The risk appetite also shows a meaningful relationship with decision confidence (r = 0.406), implying that investors willing to take calculated risks tend to be more confident in their decisions. The financial literacy correlates positively with both performance and confidence, reinforcing the importance of knowledge in making sound investment choices. The study concluded that the correlation matrix and interconnected nature of behavioural and performance-related investment factors.

Table 6: Multiple Regression Analysis – Factors Influencing Investment Performance

Dependent Variable: *Investment Performance*

Predictor Variables	Unstandardized Coefficient (B)	Standard Error	Standardized Coefficient (Beta)	t-value	Sig. (p-value)
Constant	0.842	0.241	—	3.491	0.001
Risk Appetite	0.214	0.067	0.256	3.180	0.002
Financial Literacy	0.198	0.072	0.221	2.736	0.007
Market Awareness	0.312	0.083	0.334	3.759	0.000
Decision Confidence	0.178	0.064	0.203	2.781	0.006

Model Summary:

- R = 0.718
- R^2 = 0.516
- Adjusted R^2 = 0.503
- F-value = 39.925
- Sig. = 0.000

The above table 6 shows that the multiple regression analysis explaining the extent to which behavioural factors influence investment performance among retail investors. The model is statistically significant ($p < 0.001$) and explains 51.6% of the variation in investment performance ($R^2 = 0.516$), indicating a strong explanatory power. The among predictors, market awareness ($\beta = 0.334$) has the strongest influence, suggesting that investors who actively follow market trends and financial news achieve better investment outcomes. The risk appetite ($\beta = 0.256$) and financial literacy ($\beta = 0.221$) also significantly contribute to investment performance, highlighting the role of knowledge and willingness to take calculated risks. Decision confidence ($\beta = 0.203$) similarly plays a meaningful role. The all variables are statistically significant ($p < 0.01$), reinforcing that behavioural factors jointly shape investment success.

Table 7: ANOVA – Influence of Demographics on AI Tool Adoption

Demographic Variable	F-value	Sig. (p-value)	Interpretation
Age Group	3.462	0.034*	Significant difference exists
Gender	1.128	0.289	No significant difference
Education Level	4.017	0.020*	Significant difference exists
Occupation	2.864	0.039*	Significant difference exists
Monthly Income	3.926	0.022*	Significant difference exists

Note: *Significant at 5% level (p < 0.05)*

The above table 7 evaluates whether demographic characteristics influence the adoption of AI-driven financial advisory tools. The ANOVA results reveal that age, education, occupation, and monthly income significantly impact AI adoption ($p < 0.05$). This suggests that younger individuals, highly educated respondents, private-sector professionals, and those with higher income are more likely to use AI-based investment tools. However, gender does not significantly influence AI tool adoption ($p > 0.05$), indicating that both male and female investors show similar attitudes and usage patterns toward AI financial advisory systems. The analysis suggest that demographic factors—except gender—play an important role in shaping adoption and trust in AI-driven investment platforms.

Table 8: Chi-square Test – Association Between Demographic Factors and AI Tool Usage

Demographic Variable	χ^2 (Chi-square Value)	df	p-value	Interpretation
Age Group × AI Tool Usage	12.482	4	0.014*	Significant association
Gender × AI Tool Usage	1.936	1	0.164	Not significant
Education Level × AI Tool Usage	16.305	3	0.001*	Significant association
Occupation × AI Tool Usage	10.928	3	0.012*	Significant association
Monthly Income × AI Tool Usage	14.522	3	0.002*	Significant association

Note: *Significant at 5% level ($p < 0.05$)*

The above table 8 shows that the Chi-square test results show significant associations between age, education level, occupation, and income with AI-driven investment tool usage. The study findings that the means of the younger respondents, those with higher education, private or IT-sector employees, and higher-income investors are more likely to use AI-based investment platforms. However, gender does not show a significant association, indicating that both male and female investors use AI tools at similar rates. Overall, demographic characteristics—except gender—play a meaningful role in influencing AI adoption among retail investors.

Table 9: Reliability Analysis – Cronbach's Alpha for AI Adoption and Trust Scale

Construct / Scale	Number of Items	Cronbach's Alpha (α)	Reliability Level
Perceived Usefulness	5	0.912	Excellent
Data Privacy & Security	3	0.884	Good
Social Influence & Trust	4	0.861	Good

Overall Scale Reliability	12	0.927	Excellent

The above table 9 presents the results of the reliability analysis conducted using Cronbach's Alpha, a widely accepted measure for assessing the internal consistency of multi-item scales. The result that the obtained Cronbach's Alpha value indicates a high level of reliability, confirming that the items used in the questionnaire are strongly correlated and consistently measure the intended construct. The coefficient value above 0.70 is generally considered acceptable in social science research, and the values observed in this study exceed this threshold, demonstrating that the instrument is both stable and dependable. Hence, the reliability results validate the use of the scale for further statistical analysis, including factor extraction and hypothesis testing.

Table 10: Factor Analysis – Model Summary (Extraction and Rotation)

Component (Factor)	Eigenvalue	% of Variance Explained	Cumulative %
Factor 1: Perceived Usefulness	6.248	52.071	52.071
Factor 2: Data Privacy & Security	1.443	12.028	64.099
Factor 3: Social Influence & Trustworthiness	1.045	8.709	72.808

The above table 10 provides the model summary for the factor analysis, highlighting the adequacy of the data and the proportion of variance explained by the extracted factors. The Kaiser-Meyer-Olkin (KMO) measure shows a value within the acceptable range, confirming sampling adequacy and indicating that the dataset is suitable for factor analytic procedures. Additionally, Bartlett's Test of Sphericity is statistically significant, suggesting sufficient correlations among variables for meaningful factor extraction. The total variance explained by the extracted factors demonstrates that the underlying dimensions effectively capture the major patterns in the dataset. The study findings that the factor analysis model summary validates the structural soundness of the measurement framework and supports the interpretation of the subsequent rotated factor solution.

Conclusion

The study examined the influence of Artificial Intelligence (AI)-powered investment advisory tools on the personal investment behaviour of retail investors, with a focus on young investors in Chennai. The study findings reveal that AI-driven advisory platforms—such as robo-advisors and automated portfolio management systems—are increasingly shaping investment decisions through personalised recommendations, risk assessment, and algorithm-based financial insights. The descriptive and inferential statistical results indicate strong reliability of the research instrument and highlight significant associations between demographic characteristics, awareness levels, perceived usefulness, trust, and adoption of AI-based financial tools. The result shows that the further demonstrates that AI-enabled advisory systems are perceived as convenient, efficient, and time-saving, especially among technology-oriented young investors. However, concerns related to data privacy, algorithmic transparency, and trust in automated decision-making remain important determinants influencing adoption behaviour. The factor analysis identified key underlying dimensions such as technological trust, perceived ease of use, perceived risk, and behavioural intention, which collectively shape investment behaviour in the AI-driven financial environment. The study concluded that the contributes valuable insights to the growing literature on fintech adoption and provides an analytical foundation for policymakers, academicians, and industry practitioners seeking to enhance the responsible use of AI in retail financial services.

Future of the Research

The study analysed on AI-driven financial advisory tools can expand the scope of the present research in several meaningful ways. First, increasing the sample size and extending the study across multiple cities or states will improve the generalisability of findings and enable comparative analysis across demographic groups. Second, longitudinal studies can help track changes in investor behaviour over time, offering insights into how continued exposure to AI platforms influences investment decisions and financial discipline. Third, advanced analytical techniques such as Structural Equation Modelling (SEM) or machine learning models may be applied to examine deeper relationships between behavioural, technological, and psychological variables. The study has been also addressed future research may focus on comparing human financial advisors with AI-based robo-advisors to understand differences in trust, performance, and investor satisfaction. Ethical and regulatory dimensions—such as data privacy, algorithmic transparency, and responsible AI usage—also warrant detailed exploration, given their growing relevance in fintech governance. The specific platforms like Groww, Zerodha, INDmoney, and Paytm Money can offer practical insights for product improvement. Lastly, researchers may examine the role of AI in moderating behavioural biases, including risk perception and herd behaviour, among young retail investors.

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