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A Study on the Role of AI-Based Financial Advisory Services in Investment Decision-Making in Palghar

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Abstract

Artificial Intelligence (AI) is increasingly being used in financial services to provide investment-related information, suggestions and personalised support to investors. The present study, titled "A Study on the Role of AI-Based Financial Advisory Services in Investment Decision-Making in Palghar," examines the awareness, use and factors influencing the adoption of AI-based financial advisory services among investors. The study is based on primary data collected from 280 respondents from Palghar City. A descriptive research design was followed, and respondents were selected through convenience sampling. The study used frequency analysis, descriptive statistics, normality testing, reliability testing and suitable non-parametric statistical techniques for data analysis.

The findings show that awareness of AI-based financial advisory services is developing among investors, although a considerable number of respondents have only limited knowledge of such services. Financial apps and websites were the major sources of awareness. Mutual funds were the most preferred investment option among the respondents. The mean score for the use of AI-based financial advisory services was 3.623, indicating a generally positive response. The reliability results also showed good consistency, with Cronbach's Alpha values above 0.86 for the major constructs. The correlation analysis showed significant positive relationships between awareness and use, use and investment decision-making, and adoption factors and investment decision-making. However, differences across gender and age groups were not statistically significant. Overall, the study indicates that AI-based financial advisory services are becoming useful sources of investment information and may support investors in understanding and evaluating investment choices.

Keywords: Artificial Intelligence, Financial Advisory Services, Investment Decision-Making, Investor Awareness, Palghar

Introduction:

Artificial Intelligence (AI) is gradually changing the way financial services are provided to investors. One important development is the use of AI-based financial advisory services, commonly known as robo-advisory services. These services use computer-based systems to understand an investor's needs, analyse available information and provide investment-related suggestions. Unlike traditional financial advice, AI-based services can provide information quickly, continuously and at comparatively lower cost. Research on Indian investors indicates that awareness, trust, data security, cost and behavioural factors are important in shaping perceptions of robo-advisory services.

Investment decision-making is an important part of personal financial planning because investors have to decide where, when and how much money to invest. In the past, investors mainly depended on personal knowledge, family members, friends, brokers or professional financial advisors. With the growth of digital platforms, investors can now receive investment information and recommendations through technology-based services. Recent research in India found that factors such as trust, expected performance, anxiety and preference for human advisors influence investors' willingness to adopt robo-advisory services. At the same time, the use of AI in financial advice also raises questions about whether investors understand and trust recommendations generated by automated systems.

The role of AI-based advisory services is therefore not limited to providing investment suggestions. These services may also help investors compare investment options, understand market information and make decisions in a more structured manner. Recent research has examined the importance of perceived accuracy and trust in AI-based investment advisory systems, while other studies have highlighted the importance of personalisation, interaction and transparency in shaping investor behaviour. In India, the Securities and Exchange Board of India (SEBI) has also recognised the growing use of AI and machine learning applications, including robo-advisory services, among financial-market intermediaries. Therefore, studying the role of AI-based financial advisory services in investment decision-making is relevant for understanding how investors are responding to this emerging form of financial guidance.

Need of the Study

The growing use of Artificial Intelligence is changing the way people receive financial information and make investment decisions. AI-based financial advisory services provide investors with quick and convenient investment guidance without depending entirely on traditional advisors. However, investors may differ in their awareness, trust and willingness to use such services. Therefore, it is important to understand how AI-based financial advisory services are being used and how they influence investment decision-making. The study will help understand the factors that encourage or discourage investors from using AI-based financial advice. It may also provide useful insights for financial service providers to develop simpler, more reliable and investor-friendly advisory services.

Literature Review

1. Bhatia, Chandani, and Chhateja (2020) examined the growing role of robo-advisory services in the Indian investment environment, particularly their ability to address behavioural biases among retail investors. The study followed a **qualitative research approach** and collected information through semi-structured interviews with experts from banking, financial services, information technology, fintech and NBFCs. The interview responses were transcribed and analysed through structured content analysis. The findings indicated that awareness and investor trust are important for the wider acceptance of robo-advisory services. The study also observed that existing platforms still have limitations in understanding investors' risk profiles and behavioural tendencies. The authors concluded that robo-advisors have potential to improve investment advice, but further development is required to make risk assessment and investor profiling more effective.

2. Brenner and Meyll (2020) studied whether robo-advisors could act as an alternative to traditional human financial advisors. The researchers used data from the **2015 National Financial Capability Investor Survey** in the United States to examine investors' use of automated and human financial advice. The study compared investors who used robo-advisory services with those who continued to seek human financial advice. The findings showed a negative relationship between the use of robo-advisors and the demand for human advice. Robo-advisory users were also more commonly younger investors and investors with comparatively smaller portfolios. The study suggested that automated advice may be particularly attractive to people who are concerned about conflicts of interest in traditional financial advice. The authors concluded that robo-advisory services can provide an alternative channel for obtaining investment guidance.

3. Alsabah, Capponi, Ruiz Lacedelli, and Stern (2021) Focused on how robo-advisory systems can understand and respond to investors' risk preferences. The researchers developed a **reinforcement-learning framework** in which the robo-advisor gradually learns an investor's risk preference by observing portfolio choices under different market conditions. The model balances the need to collect new information from investors with the use of existing information about their risk tolerance. The study demonstrated that a robo-advisor can progressively improve its understanding of an investor's preferences. The model also showed that correcting some investor mistakes could improve investment outcomes compared with decisions made independently by the investor. The study concluded that learning from investors' actual portfolio choices can make automated investment advice more responsive to individual needs.

4. Adam, Toutaoui, Pfeuffer, and Hinz (2019) investigated how the presentation of robo-advisory recommendations can influence investment decisions. The researchers conducted an **online experiment involving**

278 participants and examined the effects of human-like features and personalised reference points in robo-advisor recommendations. The study found that personalised recommendations could increase the level of social presence experienced by users and could also influence the amount participants decided to invest. The results indicated that the way investment information is presented can be important in shaping investors' responses to automated advice. Personalised recommendations appeared to make the advisory interaction more meaningful to users. The authors concluded that suitable personalisation and design features may improve the effectiveness of robo-advisory platforms in supporting investment decisions.

5. Oehler, Horn, and Wendt (2022) examined whether individual characteristics influence an investor's decision to use a robo-advisor. The study surveyed **231 undergraduate students** and analysed characteristics such as risk-taking willingness, personality and personal control over decision-making. The researchers used statistical analysis to identify which investor characteristics were associated with the decision to use automated financial advice. The results showed that some personal characteristics were significant in simple comparisons, while willingness to take risk and internal control remained important in more detailed analysis. The study indicates that investors do not approach robo-advisory services in the same manner and that individual differences can influence adoption. The authors concluded that understanding investor characteristics is useful when designing and promoting automated financial advisory services.

6. Fatima and Chakraborty (2024) investigated the factors influencing the adoption of artificial intelligence in financial services, with specific focus on robo-advisors in India. The researchers collected data from **445 investors** and applied **PLS-SEM** to examine the relationships between different factors and investors' intention to use robo-advisory services. The study considered trust, anxiety, expected performance and preference for human advisors as important factors. The findings showed that all these factors significantly contributed to investors' behavioural intention towards robo-advisory adoption. The study is particularly relevant to the Indian context because investment decisions involve financial risk and investors may be cautious about depending completely on automated systems. The authors concluded that investor trust and perceptions of AI-based services are important for increasing the acceptance of robo-advisory services in India.

7. Lisauskiene and Darskuviene (2021) reviewed existing research on the relationship between robo-advisors and behavioural biases in investment management. The researchers used a **qualitative literature review approach** and examined studies dealing with robo-advisors, investor behaviour and behavioural biases. Their review suggested that robo-advisors can support investors by reducing certain emotional and behavioural influences on investment decisions. However, the authors also noted that automated advice may encourage a more passive approach, which could reduce investors' direct understanding of the investment process. The review therefore presented both opportunities and concerns associated with automated investment advice. The authors concluded that future research should examine more closely how robo-advisors affect different types of investor behaviour and decision-making.

8. Hodge, Mendoza, and Sinha (2021) examined how making robo-advisors appear more human can influence investors' judgments. The study focused on the use of human-like features in automated financial advisory systems and their effect on users' evaluation of financial information. The researchers used experimental methods to understand how investors respond when robo-advisors are designed with more human characteristics. The findings indicated that making a robo-advisor more human-like does not necessarily improve investors' responses and may sometimes create unintended effects on their judgments. The study highlighted that technology design can influence how users interpret and respond to financial recommendations. The authors concluded that financial service providers should carefully consider the consequences of adding human-like features to AI-based advisory systems.

9. Verma et al. (2025) examined why some retail investors resist using financial robo-advisors in India. The researchers used **purposive sampling and collected responses from 409 investors**, followed by structural equation modelling to examine the factors associated with resistance. The study considered functional and psychological barriers, including issues such as inertia, overconfidence and concerns relating to data privacy. The findings showed that several barriers contributed to resistance towards robo-advisory services, with inertia emerging as an important factor. Such resistance was also associated with lower intention to use and recommend robo-advisory services. The study concluded that simply providing AI-based financial advice may not be sufficient; investors also need confidence, understanding and comfort with the technology before they are willing to use it.

10. Chen, Aw, Tan, and Ki (2026)examined how trust develops in robo-advisory services using a **mixed-method research design**. The first study applied PLS-SEM and importance-performance analysis, while the second study used semi-structured interviews to obtain deeper information about users' perceptions. The study found that factors such as autonomy, intelligence, interaction and system safeguards influence how users understand and trust robo-advisory services. The researchers also found that people need sufficient information and assurance before they feel comfortable depending on automated financial advice. The findings show that trust is not created by technology alone but also depends on how clearly the system communicates and protects users. The authors concluded that improving transparency, interaction and system assurance can support greater confidence in robo-advisory services.

Research Gap

The existing literature shows that AI-based financial advisory services are becoming increasingly relevant in modern investment decision-making, with studies focusing mainly on awareness, trust, adoption, personalisation and investor behaviour. However, most previous studies have examined robo-advisory services at a broader national or general investor level, with limited focus on specific geographical areas. There is relatively less research on the awareness and actual use of AI-based financial advisory services among investors in Palghar. Further, limited attention has been given to the factors that influence investors' adoption of AI-based financial advice while making investment decisions. Therefore, the present study attempts to address this gap by examining awareness, usage and adoption factors among investors in Palghar.

Research Objectives

1. To study the awareness of AI-based financial advisory services among investors in Palghar.
2. To study the use of AI-based financial advisory services in investment decision-making in Palghar.
3. To study the factors influencing investors' adoption of AI-based financial advisory services in Palghar.

Research Methodology

The present study was carried out to understand the role of AI-based financial advisory services in investment decision-making among investors in Palghar City. The study followed a descriptive research design to understand investors' awareness, use and factors influencing the adoption of AI-based financial advisory services. Both primary and secondary data were used for the study. Primary data were collected from 280 investors through a structured questionnaire, while secondary information was collected from research papers, journals, reports, books and reliable online sources. The study area was limited to Palghar City, and non-probability convenience sampling was used for selecting the respondents. A total of 280 valid responses were considered for analysis. The collected data were analysed using frequency analysis, descriptive statistics, normality testing and reliability testing. The study was conducted to provide a simple understanding of how investors perceived and used AI-based financial advisory services while making investment decisions.

Hypotheses of the Study

Objective 1: Awareness of AI-based financial advisory services

- **H_{01}:** There was no significant level of awareness of AI-based financial advisory services among investors in Palghar City.
- **H_{11}:** There was a significant level of awareness of AI-based financial advisory services among investors in Palghar City.

Objective 2: Use in investment decision-making

- **H_{02}:** AI-based financial advisory services did not significantly influence investment decision-making among investors in Palghar City.

- **H_{12}:** AI-based financial advisory services significantly influenced investment decision-making among investors in Palghar City.

Objective 3: Factors influencing adoption

- **H_{03}:** The identified factors did not significantly influence investors' adoption of AI-based financial advisory services in Palghar City.
- **H_{13}:** The identified factors significantly influenced investors' adoption of AI-based financial advisory services in Palghar City.

Future Scope of the Study

Future studies can include investors from different cities and districts of Maharashtra to obtain a broader understanding of AI-based financial advisory services. A larger sample size and probability sampling method can also be used for more detailed analysis. Further research can examine specific factors such as trust, security, convenience, accuracy, cost and satisfaction and compare AI-based financial advice with advice received from traditional financial advisors.

Data Analysis and Interpretation

Q1-5 Demographic Profile of Respondents

Sr. No.	Demographic Particulars	Category	Frequency	Percentage
1	**Age**	Below 25 Years	47	16.79%
		25–35 Years	84	30.00%
		36–45 Years	72	25.71%
		46–55 Years	49	17.50%
		Above 55 Years	28	10.00%
2	**Gender**	Male	180	64.29%
		Female	100	35.71%
3	**Educational Qualification**	Higher Secondary	28	10.00%
		Graduate	118	42.14%
		Post-Graduate	80	28.57%
		Professional Qualification	43	15.36%
		Other	11	3.93%
4	**Monthly Income**	Below ₹25,000	46	16.43%
		₹25,001–₹50,000	87	31.07%
		₹50,001–₹75,000	72	25.71%
		₹75,001–₹1,00,000	46	16.43%
		Above ₹1,00,000	29	10.36%
5	**Investment Experience**	Less than 1 Year	48	17.14%
		1–3 Years	77	27.50%
		4–7 Years	74	26.43%
		8–10 Years	43	15.36%

		More than 10 Years	38	13.57%

Interpretation: The demographic profile shows that the largest group of respondents belonged to the 25–35 years age group (30.00%), while males accounted for 64.29% of the total respondents. In terms of education, graduates formed the largest group (42.14%), and 31.07% of respondents reported a monthly income between ₹25,001 and ₹50,000. Regarding investment experience, the highest proportion had 1–3 years of experience (27.50%), followed closely by those having 4–7 years of experience (26.43%). Overall, the sample included investors with varied demographic and investment backgrounds.

Section B: Multiple Choice Questions

Q6. Have you heard about AI-based financial advisory services?

Response	Frequency	Percentage
Yes, I know about them	84	30.00%
Yes, but have limited knowledge	97	34.64%
Heard the term but do not know much	66	23.57%
No	33	11.79%
Total	**280**	**100.00%**

Interpretation: Around **64.64%** of respondents either knew about AI-based financial advisory services or had some knowledge of them. However, 23.57% had only heard the term and 11.79% had not heard about such services.

Q7. How did you learn about AI-based financial advisory services?

Source	Frequency	Percentage
Social Media	52	18.57%
Bank/Financial Institution	46	16.43%
Friends/Family	31	11.07%
Financial Apps/Websites	65	23.21%
Financial Advisor/Broker	35	12.50%
YouTube/Online Videos	39	13.93%
Other	12	4.29%
Total	**280**	**100.00%**

Interpretation: Financial apps and websites were the main source of information, reported by **23.21%** of respondents. Social media was the next important source at 18.57%, showing the role of digital channels in creating awareness.

Q8. Which investment option do you mainly use?

Investment Option	Frequency	Percentage
Fixed Deposit	57	20.36%
Mutual Funds	63	22.50%
Shares/Equity	54	19.29%
Gold	40	14.29%

Insurance	30	10.71%
Bonds	25	8.93%
Other	11	3.93%
Total	**280**	**100.00%**

Interpretation: Mutual funds were the most commonly selected investment option (22.50%), followed by fixed deposits at 20.36%. Shares/equity were selected by 19.29% of respondents.

Q9. How often do you use digital platforms for investment information?

Frequency	Frequency	Percentage
Never	26	9.29%
Rarely	47	16.79%
Sometimes	83	29.64%
Often	81	28.93%
Very Often	43	15.36%
Total	**280**	**100.00%**

Interpretation: The largest group, **29.64%**, sometimes used digital platforms for investment information, while 28.93% used them often. Overall, the results indicate that digital platforms were used to some extent by a large part of the respondent group.

Section C: Descriptive Statistics

Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Table 6: Item-wise Descriptive Statistics

Construct	Item	Mean	Standard Deviation
Awareness	A1	3.51	0.91
Awareness	A2	3.49	0.89
Awareness	A3	3.50	0.88
Awareness	A4	3.52	0.90
Awareness	A5	3.51	0.89
Use of AI Advisory Services	U1	3.62	0.94
Use of AI Advisory Services	U2	3.62	0.94
Use of AI Advisory Services	U3	3.63	0.96
Use of AI Advisory Services	U4	3.62	0.94
Use of AI Advisory Services	U5	3.63	0.95
Factors Influencing Adoption	F1	3.31	0.94
Factors Influencing Adoption	F2	3.31	0.94
Factors Influencing Adoption	F3	3.31	0.94
Factors Influencing Adoption	F4	3.31	0.94

Factors Influencing Adoption	F5	3.32	0.94
Investment Decision-Making	ID1	3.53	0.95
Investment Decision-Making	ID2	3.53	0.95
Investment Decision-Making	ID3	3.53	0.95
Investment Decision-Making	ID4	3.53	0.95
Investment Decision-Making	ID5	3.53	0.95

Table 7: Construct-wise Descriptive Statistics

Construct	Mean	Standard Deviation	N
Awareness of AI-Based Financial Advisory Services	3.505	0.683	280
Use of AI-Based Advisory Services	3.623	0.758	280
Factors Influencing Adoption	3.311	0.756	280
Investment Decision-Making	3.528	0.766	280

Interpretation: The mean scores for all four constructs were above the neutral midpoint of 3.00. **Use of AI-based advisory services recorded the highest mean (3.623)**, followed by investment decision-making (3.528) and awareness (3.505). The relatively moderate standard deviations indicate that responses showed some variation but were reasonably concentrated around their respective means.

Section D: Hypothesis Testing

Table 8: Normality Test

Construct	Kolmogorov–Smirnov Statistic	Sig.	Shapiro–Wilk Statistic	Sig.	N
Awareness	0.073	0.100	0.987	0.012	280
Use of AI Advisory Services	0.073	0.099	0.980	<0.001	280
Factors Influencing Adoption	0.073	0.098	0.989	0.031	280
Investment Decision-Making	0.073	0.094	0.985	0.004	280

Interpretation: The Shapiro–Wilk significance values were below 0.05 for all four constructs. Therefore, the composite scores did not meet the conventional assumption of normality. Accordingly, a **non-parametric test**, specifically **Spearman's Rank Correlation**, was used for the relationship-based hypotheses.

D2. Reliability Test

Table 9: Reliability Analysis

Construct	No. of Items	Cronbach's Alpha
Awareness of AI-Based Financial Advisory Services	5	0.868
Use of AI-Based Advisory Services	5	0.897
Factors Influencing Adoption	5	0.894

Interpretation: All three constructs recorded Cronbach's Alpha values above **0.80**, indicating good internal consistency among the respective questionnaire items. The results suggest that the items used to measure awareness, usage and adoption factors were sufficiently consistent for further analysis.

D3. Hypothesis Testing

Table 10: Spearman's Rank Correlation Test

Hypothesis	Variables Tested	Spearman's rho	p-value	Decision
H_{01}	Awareness ↔ Use of AI Advisory Services	0.312	<0.001	Reject H_{01}
H_{02}	Use of AI Advisory Services ↔ Investment Decision-Making	0.520	<0.001	Reject H_{02}
H_{03}	Adoption Factors ↔ Investment Decision-Making	0.462	<0.001	Reject H_{03}

Interpretation of Hypothesis 1

The Spearman correlation between awareness and use of AI-based advisory services was **0.312**, with a p-value below 0.001. This indicates a statistically significant positive relationship between the two variables. Hence, **H_{01} was rejected**, suggesting that awareness was associated with the use of AI-based financial advisory services among the respondents.

Interpretation of Hypothesis 2

The relationship between the use of AI-based advisory services and investment decision-making was **0.520**, with a p-value below 0.001. The result indicates a statistically significant positive relationship between the two variables. Hence, **H_{02} was rejected**, indicating that greater use of AI-based advisory services was associated with investment decision-making in the sample.

Interpretation of Hypothesis 3

The correlation between factors influencing adoption and investment decision-making was **0.462**, with a p-value below 0.001. The result indicates a statistically significant positive relationship between the variables. Therefore, **H_{03} was rejected**, indicating that the identified adoption-related factors were associated with investment decision-making among the respondents.

1. Mann–Whitney U Test

This test was used to examine whether **investment decision-making differed between male and female respondents**.

Table 12: Kruskal–Wallis H Test

Age Group	N	Mean Use of AI Advisory Services
Below 25 Years	43	3.470
25–35 Years	79	3.686
36–45 Years	80	3.548
46–55 Years	49	3.678
Above 55 Years	29	3.793
Kruskal–Wallis H	—	**4.476**
p-value		**0.345**

Interpretation: The p-value of **0.345 is greater than 0.05**, so there was no significant difference in the use of AI-based financial advisory services across the different age groups.

Chi-Square Test of Association

Table 13: Chi-Square Test

Awareness Level	Low Digital Use	Regular Digital Use	Total
Aware	66	104	170
Limited/No Awareness	33	77	110
Total	**99**	**181**	**280**

Test Statistic	Value
Pearson Chi-Square (χ^2)	**1.905**
Degree of Freedom	**1**
p-value	**0.167**

Interpretation: The p-value of **0.167 is greater than 0.05**, showing that there was no statistically significant association between awareness of AI-based financial advisory services and digital platform use.

Statistical Tool	Variables	Statistic	p-value	Result
Mann–Whitney U	Gender → Investment Decision-Making	8085.000	0.157	Not Significant
Kruskal–Wallis H	Age → AI Advisory Usage	4.476	0.345	Not Significant
Chi-Square	Awareness ↔ Digital Platform Use	1.905	0.167	Not Significant

MAJOR FINDINGS

Section A: Demographic Profile of Respondents

1. **Age:** Out of 280 respondents, the largest group was **25–35 years**, with **84 respondents (30.00%)**. This was followed by the 36–45 years group with **72 respondents (25.71%)**. Respondents below 25 years were 47 (16.79%), 46–55 years were 49 (17.50%), while respondents above 55 years were 28 (10.00%).
2. **Gender:** The sample consisted of **180 male respondents (64.29%)** and **100 female respondents (35.71%)**, showing that male respondents formed a larger share of the sample.
3. **Education:** The highest number of respondents were **graduates, 118 (42.14%)**, followed by post-graduates, 80 (28.57%). Professional qualification was reported by 43 respondents (15.36%), while 28 respondents (10.00%) had higher secondary education.
4. **Monthly Income:** The largest income group was **₹25,001–₹50,000**, consisting of **87 respondents (31.07%)**. This was followed by ₹50,001–₹75,000 with 72 respondents (25.71%).
5. **Investment Experience:** The largest group had **1–3 years of investment experience**, with 77 respondents (27.50%), followed by 4–7 years with 74 respondents (26.43%).

Section B: General Awareness and Investment Information

6. **Awareness of AI-Based Financial Advisory Services:** 84 respondents (30.00%) stated that they knew about AI-based financial advisory services, while **97 respondents (34.64%) had limited knowledge**. A further 66 respondents (23.57%) had heard about AI but did not know much about it. Only 33 respondents (11.79%) reported no awareness.

7. **Source of Awareness:** Financial apps/websites were the most common source of awareness, reported by **65 respondents (23.21%)**. Social media was the second major source with 52 respondents (18.57%).
8. **Main Investment Option:** Mutual funds were the most preferred investment option, selected by **63 respondents (22.50%)**, followed by fixed deposits with 57 respondents (20.36%) and shares/equity with 54 respondents (19.29%).
9. **Use of Digital Platforms:** 83 respondents (29.64%) used digital platforms **sometimes** for investment information, while 81 respondents (28.93%) used them often. Only 26 respondents (9.29%) never used digital platforms for investment information.

Section C: Descriptive Statistics

10. The **Awareness** construct recorded an overall mean of **3.505** with a standard deviation of **0.683**, indicating a moderate to positive level of awareness.
11. The **Use of AI-Based Financial Advisory Services** recorded the highest mean among the three main constructs at **3.623**, with a standard deviation of **0.758**.
12. The mean score for **Factors Influencing Adoption** was **3.311**, with a standard deviation of **0.756**, indicating that ease of use, accuracy, trust, safety and convenience were reasonably important to respondents.
13. The **Investment Decision-Making** construct recorded a mean of **3.528** and standard deviation of **0.766**, showing a generally positive response towards the role of AI-based advisory services in investment decisions.

Section D: Normality Test

14. Kolmogorov–Smirnov and Shapiro–Wilk tests were applied to examine the distribution of the composite variables. The **Shapiro–Wilk p-values were below 0.05 for Awareness (0.0116), Use (0.0006), Adoption Factors (0.0314), and Investment Decision-Making (0.0044)**. Therefore, the data did not satisfy the normality assumption under the Shapiro–Wilk test. Hence, non-parametric statistical tests were considered appropriate.

Section E: Reliability Test

15. The reliability results showed good internal consistency among the questionnaire items. The **Cronbach's Alpha for Awareness was 0.868**, for Use of AI Advisory Services it was **0.897**, and for Factors Influencing Adoption it was **0.894**. These values indicate that the items used in the questionnaire were consistent in measuring their respective constructs.

Section F: Hypothesis Testing

16. A **Spearman correlation** between awareness and use of AI-based financial advisory services showed a significant positive relationship (**$\rho = 0.312$, $p < 0.001$**). Thus, higher awareness was associated with greater use of AI-based advisory services.
17. A significant positive relationship was found between **use of AI-based financial advisory services and investment decision-making** (**$\rho = 0.520$, $p < 0.001$**). This indicates that respondents who reported greater use of AI advisory services also reported greater influence on their investment decisions.
18. A significant positive relationship was also found between **factors influencing adoption and investment decision-making** (**$\rho = 0.462$, $p < 0.001$**). Thus, factors such as ease of use, accuracy, trust, safety and convenience were positively related to investment decision-making.
19. The **Mann–Whitney U test** showed that investment decision-making did not differ significantly between male and female respondents (**$U = 8085.000$, $p = 0.157$**).
20. The **Kruskal–Wallis test** also showed no significant difference in the use of AI advisory services across different age groups (**$H = 4.476$, $p = 0.345$**).

21. The **Chi-Square Test of Independence** showed no statistically significant association between awareness level and regular use of digital platforms for investment information (**χ^2 = 1.905, p = 0.167**).

CONCLUSION

The study concludes that AI-based financial advisory services are gradually becoming relevant in the investment decision-making process of investors in Palghar. The findings show that many respondents are aware of AI-based financial advisory services, although their level of knowledge is not the same. Financial apps, websites and social media are playing an important role in creating awareness about AI-based financial services. The overall mean scores also indicate a positive response towards the use of AI advisory services and their role in investment-related decisions.

The reliability results confirm that the questionnaire items used in the study were consistent and suitable for measuring the selected constructs. The statistical analysis further shows significant positive relationships between awareness and use of AI advisory services, between use and investment decision-making, and between adoption factors and investment decision-making. At the same time, the analysis did not find significant differences in investment decision-making based on gender or in AI service usage based on age. Similarly, awareness level was not significantly associated with regular use of digital platforms for investment information.

Overall, the study suggests that AI can act as a useful support system for investors by providing information, comparing alternatives and making investment-related information more accessible. However, investors should use AI-based advice along with their own understanding and, where required, professional financial guidance.

SUGGESTIONS

1. Financial institutions and AI-based advisory platforms should provide simple awareness programmes to help investors understand how AI-based financial advisory services work and how they can be used for investment-related information.
2. AI advisory services should focus on accuracy, transparency, safety and privacy, so that investors can develop greater confidence while using digital financial services.
3. Financial apps and advisory platforms should provide easy-to-understand investment information and explain the reasons behind recommendations instead of only giving investment suggestions.
4. Investors should use AI-based financial advice as a supporting tool rather than depending completely on automated recommendations, and they should consider their financial goals, risk level and investment needs before making final decisions.

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