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Algorithmic Guidance and Investor Learning: An Empirical Examination of Robo-Advisors

Dasari Sharon¹, Dr. I. Mohana Krishna²

¹ Research Scholar, Department of BBA, KLEF, Vaddeswaram dasarisharon883@gmail.com

² Research Guide, Department of BBA, KLEF, Vaddeswaram Irrinki_mk@kluniversity.in

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ABSTRACT

Growth in robo-advisors has broadened retail access to investor-centric digital financial advice; however, it remains uncertain whether using them makes investors smart or feels smarter. This study investigates relationships between robo-adoption, digital financial literacy, financial expertise, and investment results among young and late-career retail investors in Vijayawada, Andhra Pradesh. Data were gathered with a structured, self-administered Likert-scale questionnaire; 94 effectively responded (out of 123 distributed).

Chi-square tests, one-way ANOVA, and linear regressions were computed.

Robo-adoption was significantly related to gender ($t = 4.79$, $p = .029$). Adoption, digital literacy, expertise, and outcomes were significantly different across age, gender, education, income, experience, and occupational groups. Simple regressions indicated all four hypotheses are supported: adoption predicted digital literacy ($\beta = .30$, $p = .003$) and expertise ($\beta = .32$, $p = .001$), digital literacy predicted expertise ($\beta = .26$, $p = .012$), and expertise predicted perceived investment success ($\beta = .65$, $p < .001$, $R = .43$). When adopting and learning were tested jointly, only adoption was significant.

Sub-dimension analyses indicate that the effect of adoption resides mainly in diversification awareness and information-based decision-making, while the self-perceived risktolerance and rate-of-return knowledge was slightly lower among more frequent users.

Reliability of the scales for expertise and performance outcomes was weak, and data set contains duplicate respondents, so results should be considered indicative.

Keywords: robo-advising; financial sophistication; retail investors; digital financial education; investment decision-making; India

1. Introduction

Financial technology has transformed the manner in which individual investors access financial markets. One of the key innovations in this space is what has come to be known as 'robo-advising'. Generally speaking, robo-advisors are an internet-based type of investment advisory service which, rather than relying on the long-term experience of an individual, combines computer algorithms and limited human intervention to generate investment advice and often to manage an investor's portfolio. Robo-advisors usually gather information relating to an investor's financial goals, attitudes to risk, investment horizon, and investment preferences, which it then uses to recommend or construct a portfolio of investments.

For retail investors, financial sophistication is one of the five areas in which to make good investment decisions. Being financially sophisticated can include knowing the types of financial products, understanding investment risks and return, portfolio-management skills and other financial decision-making skills. According to OECD, financial literacy is knowledge and understanding of financial concepts and risks, and the skills, confidence and motivation to apply such knowledge and understanding to make sound financial decisions (OECD, 2022). Financial sophistication is not just about understanding financial terminology but also applying what one knows when it comes to investment choices, risk management, diversification and performance measurement.

This might be the case with robo-advising as investors are exposed on an ongoing basis to recommendations and portfolio-management routines. Whereas in a conventional advisory setting, an investor could have been subject to certain degrees of advice, robo-advisors are capable of establishing a routine in terms of providing recommendations, portfolio allocation, risk analysis and investment-related information for a continuous time frame. Hao et al. (2022) observed that the implementation of robo-advising could lead to a positive spillover effect on retail investors' financial literacy, and they emphasized the role of constant interaction together with easily accessible educational content.

Growing accessibility and frequency of trading Investing in financial markets is becoming more digital and accessed online through trading websites, investing apps for mobile phones, automatic management of investments and digital sources of financial news. Still, having increased accessibility to

financial instruments does not mean investors are better equipped to use this. Having access and using financial instruments well depends on financial literacy skills (OECD, 2019).

Considering the above it is highly relevant for both academia and retail investors to study if the use of robo-advisors leads to a better understanding of financial matters by retail investors. Whether the platform is just investing on behalf of the customer.

2. Review of Literature and Research Gap

Robo-advising is an emerging digital financial advice and provides automated personal investment recommendations and portfolio management for retail investors. The existing literature on this subject largely focuses on the adoption, portfolio performance, and investor behaviour related to robo-advising, a growing interest is devoted to its possible educational function. D'Acunto and Rossi (2023) suggest that robo-advising could help investors by lowering the cognitive and financial costs of investment decisions, and it might have positive consequences for household financial literacy.

Rossi and Utkus (2020) found that robo-advising can improve portfolio diversification, asset allocation, and risk-adjusted portfolio performance of robo-investors, but the improvements could be achieved by making automated investment decisions without necessarily gaining financial knowledge.

Bianchi and Brire (2026) showed that how investors' portfolio decisions and rebalancing motivation are affected by repeated interaction, communication, and alerts of the robo-advisor, which might give investors insights to learn from the robo-advertising results. Hao et al. (2022) found more direct evidence for the financial education effect of robo-advising: robo-advising not only reduced the biases of investors' investments but also benefited the investors' financial decision-making. However, the evidence reported in Hao et al. (2022) mainly came from the Chinese market. Singh and Kumar (2025) studied the factors affecting consumers' attitudes and the adoption intention toward AI-based robo-advising services in the Indian market and found that factors such as trust, perceived usefulness, perceived risk, and perceived ease of use influence the adoption of robo-advising service.

However, previous literature has focused on the adoption of robo-advising service rather than the outcome that users will gain afterward, such as improving their financial knowledge and financial literacy, suggesting a research gap in answering the question of whether and to what extent can robo-advising enhance the financial sophistication of retail investors in the Indian context.

2.1 Adoption of robo-advisory services

Prior studies have concentrated on variables affecting intention to adopt robo-advisors, such as usefulness, ease of use, trust and perceived risk. Singh and Kumar (2025) investigated the Indian context using a modified Technology Acceptance Model on 454 valid responses from Fin Tech users and SEM. Trust, usefulness and risk positively affected attitude towards robo-advisors, attitude and ease of use affected intention to adopt, and gender moderated several effects. This paper focuses on intention to adopt rather than the post-adoption behaviour (as in this paper), in order to make different and forward-looking conclusions.

2.2 Portfolio and behavioural outcomes

D'Acunto, Prabhala and Rossi (2019) documented the implications of robo-advising for investor behaviour and portfolio outcomes – namely, increased diversification, reduced portfolio risk, and change in behavioural bias and trading behaviour. Rossi and Utkus (2020b) examined large-scale account data using machine-learning algorithms and reported that adoption decreased individual-stock and active-fund holdings, increased index-fund holdings, improved diversification and reduced risk-adjusted returns; effects varied by investor type. Bianchi and Brire (2024) found that the exchanges between investors and robo-advisory systems, such as notifications and alerts, increase investor attention and induce portfolio changes and rebalancing. These studies focus primarily on the effects of portfolio outcomes; better outcomes may be achieved because the role of advisor makes decisions for investors, rather than it makes investors learn.

2.3 The educational role of robo-advice

Hao et al. (2022) also study learning directly. Using account-level data from Ant Group and randomised advertising exposure as an instrument, they find that robo advice adoption mitigates bias in investors' portfolio management and increases style-adjusted Sharpe ratios in investors' own self-directed accounts, with larger effects for repeated investor interactions and easy access to educational content. They interpret their findings as showing that robo advice can serve as a scalable financial-education intervention. D'Acunto and Rossi (2023) review household-finance research and argue that robo advice can lower the monetary, cognitive and psychological costs of making financial decisions and help improve financial capability, but point out that direct evidence about changes in capabilities is still limited. Rossi and Utkus (2020a) also find that investors see robo advice as potentially empowering and as a means of self-improvement, while still valuing the input of human expertise. But this perceived empowerment need not translate into measurable increase in sophistication.

2.4 Access and inclusion

Reher and Sokolinski (2024) show that reducing barriers to entry increases participation and allows more investors to participate in advanced wealth-management techniques. Just being able to use advanced services does not imply that investors are becoming financially sophisticated themselves and that is why investor-level learning has to be assessed independently.

2.5 Research gap

While earlier research is clear that robo-advising has an impact on the behaviour and decisions of retail investors, the effect on increasing financial literacy remains untested. Much of the prior research has focused on areas such as portfolio performance, investment behaviour, intention to use, perceived learning and investor empowerment. However, none of the indicator areas of financial literacy such as knowledge, risk literacy, investment skills and decision-making ability are directly tested through existing measures.

Perceived learning and empowerment may simply be a falsehood of sophistication. An investor who becomes more confident may not have gained the tools to assess products, establish a risk-return trade-off or diversify. Furthermore, much of the literature is concerned with the intention of adoption and does not address what happens when investors begin using these services. Moreover, results from specific countries or investor segments may not be transferable to other markets, since levels of financial literacy, investing experience, digital awareness and advice are different. Therefore, initial evidence from retail investors in an Indian setting can offer valuable insights.

This study fills these gaps by (1) testing whether the adoption of robo-advising is related to financial sophistication, estimated in terms of knowledge about risk and return, awareness of the importance of diversification, investment comparability skills, decision-making based on information, and confidence and (2) analyzing how digital financial education moderates that relationship.

3. Conceptual Framework, Objectives and Hypotheses

The conceptual framework (Figure 1) proposes that robo-advising adoption fosters digital financial education (continuous exposure to information, portfolio reports and learning through interaction). Adoption and digital financial education in turn improve financial sophistication, which is expected to translate into better investment performance. The coefficients shown in the figure are the standardised estimates obtained in Section 5.

Standardised coefficients from simple regressions, $N = 34$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Figure 1: Conceptual framework with standardised regression coefficients

3.1 Objectives of the study

- To examine the relationship between robo-advising adoption and financial sophistication among retail investors.
- To assess the role of digital financial education in improving investors' financial knowledge and investment skills.
- To examine whether robo-advising improves investors' understanding of risk, return and portfolio diversification.
- To study the influence of robo-advising on investors' investment decision-making ability.

3.2 Hypotheses

- H1: Adoption of the robo-advice show a positive influence on digital finance education of the retail investor.
- H2: Digital financial literacy has a positive impact on the financial ducation of retail investors.
- H3: The adoption of robo-advice has a positive effect on the financial knowledge of retail investors.

4. Research

4.1 Research design

It is a quantitative, cross- sectional survey research with secondary literature. The major method instrument was structured questionnaire, and self-administration survey. Data collection and sampling The data is collected from the students and young investors of Vijayawada. The survey questionnaires sent were 123 and 94 questionnaires were kept for the analysis. The sample of the respondents was convenience sampling, and the research findings are not based on random sampling of retail investors more general, but for sample more specific.

- H4: Financial knowledge has a significant positive impact on the performance of retail investors' investments.

4. Research Methodology

4.1 Research design

This study was a quantitative, cross-sectional survey design with support from secondary sources. The questionnaire was the primary instrument.

4.2 Sampling and data collection

The data were collected from students and young investors in Vijayawada. A total of 123 questionnaires were distributed and 94 were retained for this study. Convenience sampling was used to select the respondents; this research sample is therefore not statistically representative of all retail investors.

4.3 Instrument and measurement

Questionnaire design The questionnaire comprises two sections. In Part A, we measure demographics and investing characteristics, including age, sex, level of education, occupation, monthly income, years of investing, and use of a robo-advisor. In Part B, we ask 14 questions (Q10-Q23) on a five-point Likert scale (1=strongly disagree, 5=strongly agree).

We group questions into the four constructs of the framework (Table 1).

We formatted several items as text responses (e.g. Strongly Agree) into the question, but we removed respondent names before analysis.

Table 1: Constructs, items and reliability

Construct	Items	No. of items	Cronbach's α
Robo-advising adoption (RA)	Q10 use for decisions; Q11 regular use; Q12 trust; Q13 convenience	4	0.81
Digital financial education (DFE)	Q14 useful information; Q15 portfolio reports; Q16 learning through interaction	3	0.92
Financial sophistication (FS)	Q17 risk–return; Q18 diversification; Q19 compare options; Q21 consider risk–return; Q22 information not emotion	5	0.21
Investment performance (IP)	Q20 better decisions; Q23 confidence after use	2	-0.09

Construct score = mean of its items. Investment performance is self-perceived, not measured returns.

Alpha values indicate good-to-excellent consistency for RA and DFE but very low consistency for FS and IP. The FS items split into two clusters (Q17, Q19, Q21 versus Q18, Q22), and the two IP items are essentially uncorrelated ($r = -.04$). Results involving FS and IP must therefore be read with caution; Section 5.7 examines the FS sub-dimensions separately.

4.4 Statistical tools

Descriptive statistics, Cronbach's alpha and Pearson correlations.

Chi-square test of independence (including Cramer's V) (which investigated the relationship between demographic variables and who uses, and who does not use a robo-advisor). Categories with low expected counts were collapsed; checked Yates' correction and Fisher's exact test for 2 X 2 tables.

Were also used. - One-way ANOVA (Levene's test, eta-squared, Tukey post-hoc and Kruskal-Wallis as a non-parametric check) to compare construct scores across demographic groups.

Simple and multiple linear regression were used to test H1-H4, along with Durbin-Watson and variance inflation factor tests.

Analyses were carried out in Python and are presented in documentation, including formulas in Excel and menu paths in SPSS to replicate, in the following workbook. Significance level is 5%.

5. Data Analysis and Results

5.1 Profile of respondents

Table 2: Demographic profile (N = 94)

Measure	Age	Gender	Education	Occupation	Monthly Income	Investment Experience	Used a Robo-advisor
Category 1	Below 25: 69 (73.4%)	Female: 59 (62.8%)	High School: 4 (4.3%)	Student: 60 (63.8%)	Below ₹20,000: 60 (63.8%)	Less than 1 year: 74 (78.7%)	Yes: 48 (51.1%)
Category 2	25–34: 25 (26.6%)	Male: 35 (37.2%)	Undergraduate: 71 (75.5%)	Salaried Employee: 18 (19.1%)	₹20,000–₹40,000: 18 (19.1%)	1–3 years: 17 (18.1%)	No: 46 (48.9%)
Category 3	—	—	Postgraduate: 19 (20.2%)	Business/Self-employed: 7 (7.4%)	₹60,001–₹1,00,000: 13 (13.8%)	4–6 years: 3 (3.2%)	—
Category 4	—	—	—	Professional: 3 (3.2%)	Above ₹1,00,000: 3 (3.2%)	—	—
Category 5	—	—	—	Other: 6 (6.4%)	—	—	—

The sample is young (73.4% below 25), mostly female (62.8%), predominantly undergraduate (75.5%) and student (63.8%), with low incomes and short investing histories (78.7% under one year). About half (51.1%) reported having used a robo-advisory service.

5.2 Descriptive statistics and correlations

Table 3: Descriptive statistics and Pearson correlations

Construct	Mean	SD	RA	DFE	FS	IP
RA	2.93	0.87	—	0.30	0.32	0.50
DFE	3.53	0.94	0.30	—	0.26	0.44
FS	3.59	0.48	0.32	0.26	—	0.65
IP	3.51	0.54	0.50	0.44	0.65	—

All correlations are significant at $p < .05$ (RA–DFE $r = .30$, $p = .003$; DFE–FS $r = .26$, $p = .012$).

Adoption has the lowest mean (2.93), indicating moderate and uneven use of robo-advisors in this sample, whereas digital financial education (3.53), sophistication (3.59) and perceived performance (3.51) are above the scale midpoint. At item level, respondents most strongly agreed that they consider risk and return before investing (Q21, $M = 4.02$) and can compare options (Q19, $M = 4.01$), and were least positive about basing decisions on information rather than emotion (Q22, $M = 2.85$) and understanding diversification (Q18, $M = 3.15$).

5.3 Chi-square tests: demographics and robo-advisor usage

H0: robo-advisor usage is independent of the demographic variable. Table 4 reports Pearson chi-square tests using merged categories where needed so that expected counts are adequate.

Table 4: Chi-square tests of independence with robo-advisor usage

Enrollment in local colleges, 2005

Statistical Measure	Age	Gender	Education	Income	Experience	Occupation
χ^2	2.28	4.79	2.87	1.02	3.65	1.02
df	1	1	1	2	1	2
p-value	.131	.029*	.090	.599	.056	.599
Cramér's V	0.16	0.23	0.17	0.10	0.20	0.10
Min. expected	12.2	17.1	9.3	7.8	9.8	7.8
Decision	Not significant	Significant	Not significant	Not significant	Not significant	Not significant

* $p < .05$. Un-merged tables for education, income, experience and occupation are in the workbook.

Gender is the only variable with a significant association: 65.7% of men (23/35) reported using a robo-advisor compared with 42.4% of women (25/59); the effect is small-to-moderate ($V = .23$). The result holds with Yates' correction ($\chi^2 = 3.90$, $p = .048$) and Fisher's exact test ($p = .034$, odds ratio = 2.61). Experience ($p = .056$) and education ($p = .090$) show a tendency for more experienced and postgraduate respondents to be users but do not reach significance. Before merging, the tests for education ($\chi^2(2) = 7.68$, $p = .022$), experience ($\chi^2(2) = 10.57$, $p = .005$) and occupation ($\chi^2(4) = 10.03$, $p = .040$) appeared significant, but one-third or more of their cells had expected counts below 5 (for example, all 4 high-school respondents, all 7 business owners and all 3 professionals were users), so those p-values are unreliable.

5.4 One-way ANOVA: differences in construct scores

H0: mean construct scores are equal across the groups of the demographic factor. Table 5 summarises the F-tests; eta-squared appears in brackets.

Table 5: One-way ANOVA F-values (η^2) by demographic factor

Outcome Measure	Age (2 groups)	Gender (2 groups)	Education (3 groups)	Income (4 groups)	Experience (3 groups)	Occupation (5 groups)
Adoption (RA)	51.72*** (0.36)	33.46*** (0.27)	23.03*** (0.34)	21.88*** (0.42)	10.95*** (0.19)	21.21*** (0.49)
Digital financial education	7.64** (0.08)	8.63** (0.09)	5.94** (0.12)	6.21*** (0.17)	1.50 (0.03)	9.08*** (0.29)
Financial sophistication	4.31* (0.04)	4.10* (0.04)	3.24* (0.07)	0.94 (0.03)	6.64** (0.13)	3.21* (0.13)
Investment performance	12.64*** (0.12)	24.29*** (0.21)	11.64*** (0.20)	4.72** (0.14)	17.55*** (0.28)	4.84** (0.18)

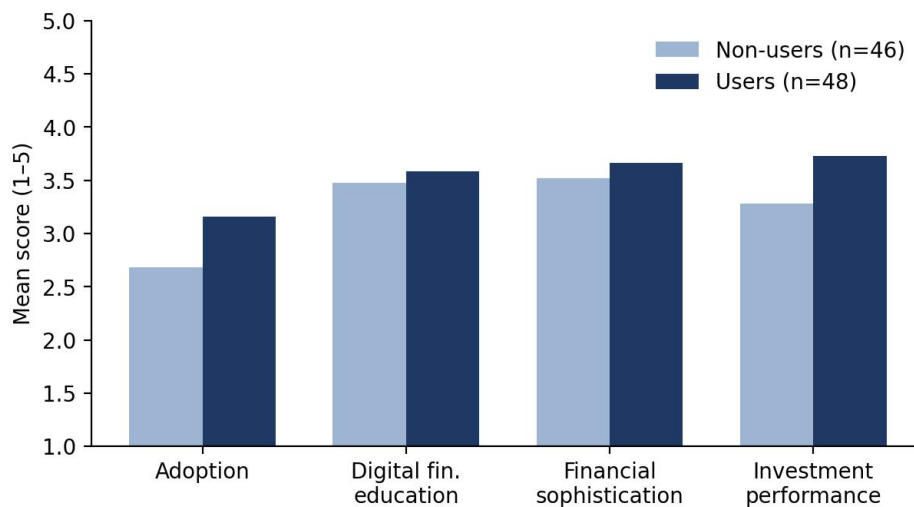
* $p < .05$, ** $p < .01$, *** $p < .001$. Kruskal–Wallis test results are in the workbook.

Table 6: Financial sophistication (FS) by group: mean and SD

Demographic Variable	Category	n	Mean	SD
Age	Below 25	69	3.53	0.49
	25–34	25	3.76	0.44
Gender	Female	59	3.52	0.50
	Male	35	3.72	0.42
Education	High School	4	3.80	0.40
	Undergraduate	71	3.52	0.50
	Postgraduate	19	3.81	0.37
Experience	Less than 1 year	74	3.52	0.50
	1–3 years	17	3.95	0.19
	4–6 years	3	3.40	0.00
	7+ years	0	0.00	0.00
Occupation	Student	60	3.55	0.50
	Salaried Employee	18	3.63	0.47
	Business/Self-employed	7	4.00	0.00
	Professional	3	4.00	0.00
	Other	6	3.20	0.22

Financial sophistication differed significantly by age ($F(1,92) = 4.31, p = .041$), gender ($F(1,92) = 4.10, p = .046$), education ($F(2,91) = 3.24, p = .044$), experience ($F(2,91) = 6.64, p = .002$) and occupation ($F(4,89) = 3.21, p = .016$), but not by income ($F(3,90) = 0.94, p = .425$). Older respondents (25–34), men, postgraduates and respondents with 1–3 years of experience scored higher. Tukey's test showed that the only significant pairwise difference in experience was between 1–3 years and under one year (mean difference = 0.44, $p = .002$); the 4–6 year group has only three respondents. The effect sizes for FS are small to medium ($\eta^2 = .04-.13$).

Adoption and perceived investment performance differed even more strongly across groups. Adoption was higher among respondents aged 25–34 ($M = 3.79$ vs 2.61), men (3.51 vs 2.58), postgraduates (3.84 vs 2.75 for undergraduates) and those with higher incomes (η^2 up to .42 for income and .49 for occupation). Digital financial education was significantly higher for older respondents, men, postgraduates and higher earners, but did not vary by experience ($p = .229$). Notably, respondents who had used a robo-advisor rated their investment performance higher than non-users ($M = 3.73$ vs 3.28 ; $F(1,92) = 19.32, p < .001, \eta^2 = .17$), whereas differences in FS (3.66 vs $3.52, p = .145$) and DFE ($p = .589$) were not significant (Figure 2).

**Figure 2: Mean construct scores for robo-advisor users and non-users**

Levene's test indicated unequal variances for several comparisons (for example, FS by experience and occupation), and group sizes are very unbalanced, so the Kruskal–Wallis test was also run. It agreed with the ANOVA decisions for all FS comparisons. Because 28 ANOVAs were run, a few marginal results (p between .03 and .05) could arise by chance and should be read with caution.

5.5 Regression analysis: testing H1–H4

Table 7: Simple linear regression results (N = 94)

Hyp.	Path	B	SE	β	t	p	R ²	F
H1	RA → DFE	0.325	0.107	0.303	3.05	.003**	0.092	9.28
H2	DFE → FS	0.133	0.052	0.258	2.56	.012*	0.067	6.57
H3	RA → FS	0.179	0.054	0.325	3.29	.001**	0.105	10.84
H4	FS → IP	0.732	0.088	0.655	8.31	< .001***	0.429	69.07

** $p < .01$, *** $p < .001$. Durbin–Watson values 1.77–2.44 (no serious autocorrelation).

H1 (RA → DFE): adoption significantly predicts digital financial education ($B = 0.325$, $\beta = .303$, $t = 3.05$, $p = .003$), explaining 9.2% of its variance. H1 is supported.

H2 (DFE → FS): digital financial education significantly predicts sophistication ($B = 0.133$, $\beta = .258$, $p = .012$; $R^2 = .067$). H2 is supported, although the effect is small.

H3 (RA → FS): adoption significantly predicts sophistication ($B = 0.179$, $\beta = .325$, $p = .001$; $R^2 = .105$). H3 is supported.

H4 (FS → IP): sophistication is a strong predictor of perceived investment performance ($B = 0.732$, $\beta = .655$, $p < .001$), explaining 42.9% of its variance. H4 is supported.

Both predictors were then entered together to predict FS (Table 8).

Table 8: Multiple regression: FS on RA and DFE

Predictor	B	SE	β	t	p
Constant	2.833	0.214	—	13.27	< .001***
Robo-advising adoption (RA)	0.150	0.057	0.271	2.65	.009**
Digital financial education (DFE)	0.091	0.053	0.176	1.72	.089

$R^2 = 0.134$, adjusted $R^2 = 0.115$, $F(2,91) = 7.02$, $p = 0.0015$; $VIF = 1.10$.

The model is significant and explains 13.4% of the variance in FS. Adoption remains a significant predictor ($\beta = .271$, $p = .010$) but digital financial education does not ($\beta = .176$, $p = .089$) once adoption is controlled. The indirect effect of adoption through education ($0.325 \times 0.091 = 0.029$) is not significant (Sobel $z = 1.50$, $p = .134$). Digital financial education is thus correlated with sophistication but adds little independent explanatory power beyond adoption in this sample.

5.6 Summary of hypothesis testing

Table 9: Hypothesis decisions

Hypothesis	Statistic	Decision
H1: RA → DFE	$\beta = .303$, $p = .003$	Supported
H2: DFE → FS	$\beta = .258$, $p = .012$	Supported (small effect; not significant when RA is controlled)
H3: RA → FS	$\beta = .325$, $p = .001$	Supported
H4: FS → IP	$\beta = .655$, $p < .001$	Supported

5.7 Supplementary analysis: what drives the adoption–sophistication link?

Because the FS scale had low reliability, its two item clusters were analysed separately. The first, “analytical knowledge” (Q17, Q19, Q21: risk–return understanding, comparing options, considering risk and return), is reasonably consistent ($\alpha = .76$; $M = 3.99$). The second, “diversification and rational decision-making” (Q18, Q22), has two items correlated at $r = .47$ ($M = 3.00$).

Table 10: Regression of FS sub-dimensions on adoption and education

Outcome	Predictor	B	r	p	R ²
Analytical knowledge (Q17, Q19, Q21)	RA	−0.239	−.303	.003	.092
	DFE	0.185	.251	.015	.063
Diversification & rational decisions (Q18, Q22)	RA	0.808	.706	< .001	.499
	DFE	0.055	.052	.620	.003

The positive H3 result is therefore driven entirely by the second cluster: heavier robo-advisor users report better diversification awareness and more information-based (less emotional) decision-making ($r = .71$), while their self-rated risk–return knowledge and comparison ability are slightly lower ($r = -.30$). One plausible reading is that people who rely on automated advice feel less need to analyse options themselves, or that non-users overstate their analytical skills. Digital financial education is positively related to analytical knowledge but unrelated to the diversification cluster. Likewise, the strong FS → IP link (H4) is carried by the second cluster ($r = .63$ with IP) rather than by analytical knowledge ($r = .16$, $p = .136$). The IP item on confidence after using robo-advising (Q23) is itself correlated with adoption ($r = .51$), which means part of H4 reflects shared method rather than independent effects.

5.8 Robustness: repeated respondent entries

On closer inspection, we find just 28 unique respondent names out of the 94 lines and a large number of lines with identical demographic description and almost identical responses. This strongly indicates identical questionnaires submitted by same respondents (or file duplication), which would explain the reported 94 usable lines. Re-estimating H1–H4 using 28 respondent names ($n=28$) yields the following (significant p value in bold): H1=.27, $p=.247$; H2=.28, $p=.181$; H3=.38, $p=.049$; H4=.70, $p<.001$.

While the directions of all effects are unaffected, the small samples find two tests of H1 and H2 to be insignificant.

Duplicate entries actually make the p values for all tests too optimistic, since all tests used above are based on the assumption of independent observations. Please check the raw responses and count of “94 usable” for submission.

6. Discussion

The results provide some support to the hypothesis that robo-advising correlates with a higher level of financial sophistication for young retail investors. Adoption correlates positively with digital financial education (H1), as Hao et al. (2022) theorize, since the user repeatedly encounters platform and learning content. Adoption correlates positively with sophistication (H3) and emerges as the stronger of the two predictors in the combined test, while digital financial education alone correlates weakly (H2) before adoption is controlled for. In this sample, the platform's influence is higher than that of the user experience, which includes receiving educational content.

Objective 3 (risk, return and diversification): the answer is mixed. The evidence shows improved diversification awareness, but not better self-estimated risk/return analysis. This finding remains in line with the warning of D'Acunto, Prabhala and Rossi (2019), and Reher and Sokolinski (2024), that improved portfolio structure and increased availability of sophisticated services may do nothing to ensure investors to develop independent analytical skill. Objective 4 (decision-making): information-based decision-making increases with adoption, and no relation is found to the self-estimated variety of the sophistication scale to perceived investment performance (H4) again, with the performance index based on subjects' subjective assessment.

The demographics suggest a digital-advice divide, as Singh and Kumar (2025) found gender to be a moderator of robo-advisor attitudes. Among those shown to have been most likely to adopt the product and to score the highest on educational metrics are: respondents who are male, falls within the older (25–34) age group, has a higher than average level of education, and has a higher income. Gender was the only characteristic to have a statistically significant correlation with product usage according to chi-squared analysis.

7. Implications

For the platform/adviser: also include embedded explanations of risk–return trade-offs and “why this recommendation” cues, as understanding of diversification is high but analysis skills are unlikely to increase with use.

For Educators and Regulators: Incorporate robo-advisory tools in to structured financial education, especially to female users and novice and lower income investors, who tend to use them less.

For investors: robo-advice is an addition to, not a substitute for, knowledge about risk and return.

8. Limitations and Future Research

Repeated respondent recordings: 28 unique names in 94 rows; [replicates destroy independence and increase significance] This needs to be fixed before it is published.

The FS and IP scales are unreliable; future studies should rely on validated multiple-item financial-literacy assessments with correct/incorrect responses that assess actual versus perceived sophistication.

All variables are self-report, are measured at a single point in time, do not indicate causality and all are subject to common-method bias.³ Non-users responded to the adoption items, so the RA scale indicates attitudes towards robo-advice as well as usage.

Sample Convenience sample of young students in one city with small cells for some categories; generalisation is limited.

Future researches should consider use of pre/post or longitudinal design, larger random sample, structural equation modelling, and portfolio data.

9. Conclusion

This research tested the impact of robo-advising adoption, digital financial literacy, financial sophistication and investment performance of 94 retail investors in the city of Vijayawada. Hypotheses 1, 2, 3 and 4 were all supported in simple regressions, some significance emerged between gender and robo-advisor adoption, and construct scores differed by age, gender, education, experience and occupation. Adoption was a better predictor of sophistication than digital financial literacy, gains were seen more in diversification and disciplined decision-making than in analytical knowledge, and the well-known issues of the problematic measures adopted and its sample-generalizing power are reminders to avoid facile conclusions. The finding that robo-advising can be a useful, natural ally for investor education is promising, but robust evidence is still lacking to confirm that robo-advisors successfully enhance retail investors' financial literacy.

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