

Financial Literacy and AI-Enabled Investment Tools as Socio-Technical Resources: Investment Behaviour among Salaried Employees

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Abstract

This study examines how financial literacy and familiarity with artificial-intelligence (AI)-enabled financial tools are associated with the investment behaviour of salaried employees. Financial literacy and AI engagement are treated as complementary socio-technical resources that can shape how individuals understand risk, interpret financial information and participate in digital investment environments. A structured online questionnaire generated 300 responses, of which 295 complete cases were analysed using descriptive statistics, Pearson correlations and SPSS regression/ANOVA outputs. The most interpretable results show a strong association between understanding investment risk and regular investing ($F(1,293)=909.268$, $p<.001$, $R^2=.756$), while two AI-related perceptions—familiarity with AI in financial decision-making and the belief that AI simplifies complex financial concepts—are jointly associated with regular investment activity ($F(2,292)=4406.231$, $p<.001$, $R^2=.968$). However, several financial-literacy items display perfect inter-item correlations and some ANOVA outputs omit F and p values, so broader inferential claims are deliberately limited. The study contributes by linking financial capability with AI-mediated investing among salaried employees while demonstrating the importance of measurement quality, transparent interpretation and replication in research on digital financial behaviour.

Keywords: financial literacy; artificial intelligence; investment behaviour; salaried employees; digital finance

Introduction

Personal investing has become increasingly intertwined with digital platforms. Mobile brokerage applications, automated portfolio tools, data-driven recommendation systems and conversational financial assistants can lower the practical barriers to participating in financial markets. At the same time, these technologies shift more interpretive responsibility towards individuals. Investors must decide not only what to buy or sell but also when to trust a platform, how to evaluate an automated recommendation and whether the apparent precision of a digital interface corresponds to sound financial judgement. The social significance of this change is especially visible among salaried employees, who often combine relatively regular income with limited time for specialised financial education and growing exposure to app-based financial services.

Financial literacy remains an important resource in this environment. It is commonly understood as the knowledge and capability required to interpret financial concepts, assess risk and make decisions that are consistent with longer-term objectives. Research has linked financial literacy to saving, retirement planning and participation in investment markets (Lusardi and Mitchell 2014; van Rooij et al. 2011). Recent evidence from India similarly suggests that financial literacy and digital financial literacy are associated with investment behaviour and financial participation (Ravikumar et al. 2022; Shroff 2024; Yadav and Banerji 2025). These studies indicate that access to digital finance does not eliminate the need for financial knowledge. Rather, knowledge may become more important as the range and speed of financial choices expand.

Artificial intelligence (AI) adds a second layer to this problem. In consumer finance, AI can appear through portfolio recommendation engines, automated risk profiling, chat-based advisory interfaces, personalised alerts and algorithmic decision support. Technology acceptance research shows that users are more likely to adopt digital systems when they perceive them as useful and manageable (Davis 1989; Venkatesh et al. 2003). Research on robo-advisory adds that trust, perceived expertise, social influence, privacy and the design of the advisory interaction shape whether automated financial guidance is accepted (Belanche et al. 2019; Hildebrand and Bergner 2021; Lourenço et al. 2020; Seiler and Fanenbruck 2021). Financial literacy may therefore affect investment behaviour directly and may also influence how effectively people engage with AI-enabled tools.

This study examines these domains together: financial literacy, AI-related financial decision support and the investment behaviour of salaried employees. The dataset contains 300 returned questionnaires and 295 complete cases. The available statistical outputs also contain unusually high, in several cases perfect, correlations among self-reported financial-literacy items and several ANOVA tables for which F statistics and significance values are absent. These outputs should not be treated as evidence that every hypothesised relationship is significant. Accordingly, the analysis retains only interpretable empirical results, makes the data-quality limitations explicit and frames the contribution as an exploratory socio-technical account of how financial capability and AI-related engagement may operate together.

The article addresses three research questions. First, what is the demographic and investment-behaviour profile of the salaried employees represented in the survey? Second, to what extent is self-reported understanding of investment risk associated with regular investment activity? Third, to what extent are AI familiarity and the perceived ability of AI to simplify complex financial concepts associated with regular investment activity? These questions are deliberately narrower than a causal claim. The study is cross-sectional, uses self-reported measures and does not observe realised portfolio returns or experimentally manipulate AI exposure.

The main contribution is twofold. Substantively, the study treats financial literacy and AI-related financial engagement as complementary socio-technical resources rather than competing explanations of investment behaviour. Methodologically, it demonstrates the importance of distinguishing a visually impressive statistical output from an interpretable one. For social-science research on digital finance, both points matter: technology can expand individual capability, but the quality of inference depends on how constructs are measured, how samples are constituted and how statistical evidence is reported.

Financial literacy as a capability for investment participation

Financial literacy can be conceptualised as a form of human capital that supports economic decision-making. Lusardi and Mitchell (2014) argue that financial knowledge has consequences for individual welfare because it affects the ability to understand intertemporal choices, inflation, interest rates and risk. In investment settings, literacy is particularly relevant because market participation requires individuals to evaluate uncertain future outcomes and to distinguish diversification from simple product familiarity. Van Rooij et al. (2011) show that lower financial literacy is associated with a lower likelihood of stock-market participation, reinforcing the idea that knowledge is not merely descriptive but behaviourally consequential.

For salaried employees, the practical content of financial literacy includes setting goals, understanding the risk-return relationship, recognising diversification, reviewing investments and deciding when professional advice is needed. These competences can affect whether regular income is translated into active saving and investment. The Indian evidence is consistent with this interpretation. Shroff (2024) finds that financial literacy is related to investment decisions among Indian investors, while Yadav and Banerji (2025) report that digital financial literacy is

positively related to saving and investment behaviour. Ravikumar et al. (2022) further emphasise that digital financial literacy is multidimensional and includes not only financial knowledge but also the ability to operate safely and effectively in digital financial environments.

Financial literacy should nevertheless not be treated as a guarantee of superior investment performance. Much of the literature measures knowledge, confidence, intention or participation rather than realised risk-adjusted returns. Moreover, subjective literacy can diverge from objective literacy. This distinction matters in the context of AI because confidence in one's own financial knowledge may encourage technology adoption even when objective knowledge is limited. Choo et al. (2023), for example, find that robo-advisor adoption is more strongly associated with subjective than objective financial literacy in their Taiwanese sample. The implication is that research should separate capability, confidence and actual performance rather than treating them as interchangeable.

AI-enabled financial tools and technology acceptance

The Technology Acceptance Model proposes that perceived usefulness and perceived ease of use are central determinants of technology acceptance (Davis 1989). UTAUT extends this approach by incorporating performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al. 2003). These frameworks are useful for financial applications because an AI-enabled investment tool is not adopted solely because it is technically sophisticated. Users must believe that it helps them perform a meaningful task, that they can understand or operate it and that the surrounding institutional conditions are acceptable.

Evidence from automated financial advice supports this socio-technical view. Belanche et al. (2019) show that attitudes and subjective norms help explain potential users' adoption of robo-advisors. Seiler and Fanenbruck (2021) identify perceived usefulness and privacy as important predictors of intention to use digital investment solutions. Lourenço et al. (2020) demonstrate that acceptance of automated financial advice is affected by perceived trust and expertise, while Hildebrand and Bergner (2021) show that conversational design can increase affective trust and recommendation acceptance. Zhang et al. (2021) similarly find that consumers distinguish between human and robo-advisors in terms of trust and expected performance.

These findings suggest that "AI adoption" is not a single technical event. It is a relationship between users, interfaces, institutions and decision contexts. In the present survey, the AI-related

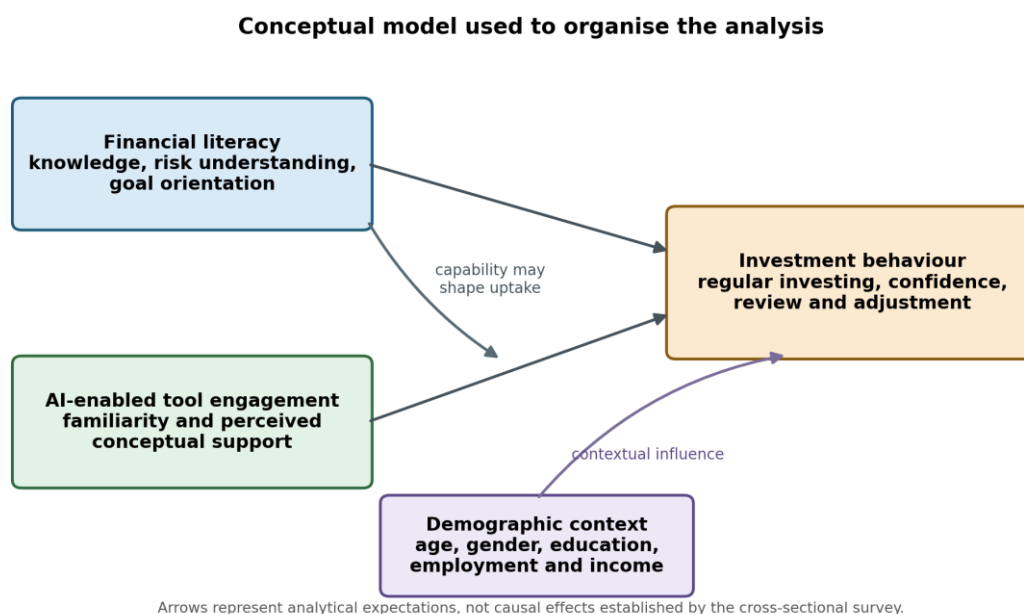
measures are relatively narrow: familiarity with the use of AI in financial decision-making and the perception that AI makes complex financial concepts easier to understand. These items are best interpreted as indicators of AI-related engagement and perceived usefulness, not as evidence of sustained robo-advisor usage or delegated portfolio management.

Complementarity between financial capability and AI engagement

The conceptual expectation of this study is that financial literacy and AI-enabled tools can be complementary. Financial literacy gives users a basis for evaluating risk, setting objectives and questioning recommendations. AI tools can lower information-processing costs, organise information and make complex material more accessible. When the two are combined, an employee may be better positioned to use digital finance actively without fully delegating judgement to the system. Conversely, a user with low financial capability may have difficulty assessing whether an apparently personalised AI recommendation is appropriate, while a financially knowledgeable user who distrusts or cannot use digital tools may fail to benefit from technological support.

This complementarity also has a social dimension. Age, gender, education, employment context and income can shape both financial learning opportunities and access to digital tools. The present sample is concentrated among younger adults, men, private-sector employees, graduates and middle-income earners. Such a sample may represent a group with relatively high exposure to digital services but it does not represent the full range of salaried workers. Demographic variables are therefore treated as contextual characteristics rather than as causal moderators in the present analysis.

Figure 1. Structural model of financial literacy, AI-enabled tool engagement and investment behaviour



Note: The arrows represent analytical expectations, not causal effects established by the cross-sectional survey.

Methodology

Research design and sample

This article is based on primary survey data collected with a structured online questionnaire distributed to salaried employees. The questionnaire collected demographic information together with items on financial literacy, investment practices and AI-related financial decision support. A total of 300 responses were returned. Across the SPSS frequency tables, five cases are marked as missing and 295 cases are reported as valid. The analysis therefore uses $n=295$ as the complete-case sample for the reported models.

The available documentation does not identify a probability-based sampling frame. The sample should therefore be interpreted as a non-probability online sample rather than as a statistically representative sample of all salaried employees. This distinction is important because the respondent profile is highly concentrated: most valid respondents are aged 25–34, male, privately employed, university educated and within the reported middle-income band. These characteristics are described in the Results section and used to delimit the scope of inference.

Measures

The questionnaire includes several groups of self-reported items. Investment-behaviour items include regular investment in financial instruments, setting specific financial goals, confidence in making one's own investment decisions, self-identification as a risk taker, frequent review and adjustment of investments and reliance on professional financial advice. The SPSS output reports a mean of 4.79 for regular investment and means of 4.58 for several other investment-behaviour statements. The precise response anchors are not available in the study materials, so the analysis does not infer a scale range beyond the values shown in the SPSS output.

Financial-literacy-related items include actively seeking to improve financial literacy, perceived improvement of financial literacy through AI tools, the belief that improved financial literacy increases long-term financial security, financial confidence in investment decision-making and understanding of risks associated with different types of investments. AI-related variables used in the interpretable regression output are familiarity with AI in financial decision-making and the perception that AI makes complex financial concepts easier to understand.

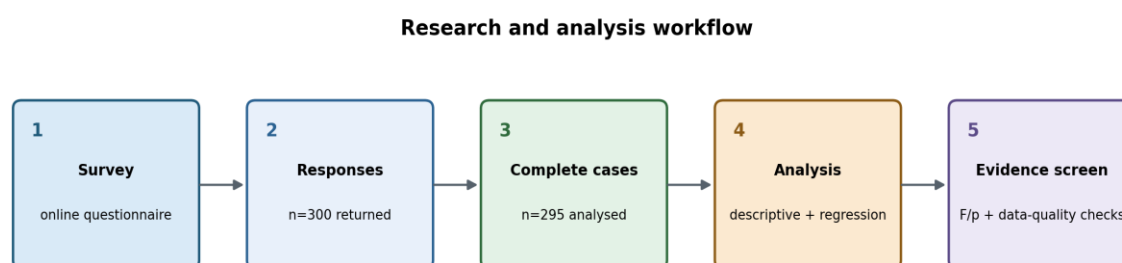
Because the questionnaire is not documented as a previously validated scale and because the correlation matrix shows perfect pairwise correlations among several financial-literacy items, the constructs are treated as individual indicators rather than as a validated latent scale. This conservative treatment avoids assuming that the items establish a single broad financial-literacy construct without independent evidence of reliability and construct validity.

Analytical strategy

The SPSS outputs include frequency tables, descriptive statistics, Pearson correlations and ANOVA tables associated with linear regression models. The analysis follows a conservative evidence rule. Descriptive statistics are retained where the values are clearly reported. Inferential interpretations are made only when the relevant ANOVA output provides degrees of freedom, an F statistic and a significance value. For the two complete regression ANOVA tables, R^2 is reconstructed from the reported regression and total sums of squares as a transparent descriptive measure of model fit.

The first interpretable model uses “I regularly invest in financial instruments” as the dependent variable and “I understand the risks associated with different types of investments” as the predictor. The second uses the same dependent variable with two AI-related predictors: “AI makes it easier for me to understand complex financial concepts” and “I am familiar with the use of AI in financial decision-making”. Several additional ANOVA tables report a regression sum of squares of 249.715, zero residual sum of squares and no F or significance statistic. Those models are not treated as evidence of statistical significance.

Figure 2. Research and analysis workflow



Five incomplete records were excluded; inferential claims are limited to models with reported F and p values.

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Data-quality considerations

The correlation matrix deserves particular attention. Five financial-literacy-related statements have pairwise Pearson coefficients of 1.000 with $p < .001$. Perfect correlations across multiple conceptually distinct items are statistically unusual in survey data. They can occur when variables are duplicated, recoded from the same source, entered identically or generated by a data-processing error. They can also signal that respondents gave exactly the same response to every item, although perfect agreement across all 295 cases would itself require investigation. The present article therefore treats the matrix as a data-quality diagnostic rather than as substantive proof of strong associations.

A second concern is the repeated appearance of identical regression sums of squares with zero residual variance in models for different dependent variables. When residual variance is zero, standard inferential statistics can become undefined, which is consistent with the missing F and significance values in the displayed output. The appropriate response is not to infer

significance from the regression sum of squares alone. The raw data should therefore be rechecked for duplicate columns, coding errors, missing-value handling and the exact response scale. Two models contain complete inferential statistics and are retained for exploratory interpretation; claims based on incomplete outputs are excluded.

Results

Respondent profile

Among the 295 valid cases, 68.1% are aged 25–34, 20.7% are aged 35–44, 10.8% are aged 45–54 and 0.3% are aged 55 or above. Men account for 79.3% of valid responses and women for 20.7%. Private-sector employees represent 79.7% of the valid sample and public-sector employees 20.3%. Educational attainment is also high: 68.1% report an undergraduate degree, 20.7% postgraduate education, 10.8% a doctorate and 0.3% education up to the 10th standard. The dominant monthly-income category is 50,000–100,000, containing 79.0% of valid respondents.

This profile shows that the study mainly captures a younger, male, private-sector and relatively well-educated segment of salaried employees. It is therefore inappropriate to interpret the results as a demographic portrait of the salaried workforce as a whole. Instead, the profile describes the social location of the observed relationships. It also helps explain why digital financial services and AI-related investment tools may be salient to the respondents: the sample is concentrated in groups likely to have frequent exposure to digital platforms.

Table 1. Demographic profile of valid respondents (n=295)

Characteristic	Category	n	Valid %
Age	25–34	201	68.1
Age	35–44	61	20.7
Age	45–54	32	10.8
Age	55 and above	1	0.3
Gender	Female	61	20.7
Gender	Male	234	79.3
Employment sector	Public	60	20.3
Employment sector	Private	235	79.7
Education	10th standard	1	0.3
Education	Undergraduate	201	68.1
Education	Postgraduate	61	20.7
Education	Doctorate	32	10.8
Monthly income	Up to 50,000	1	0.3
Monthly income	50,000–100,000	233	79.0
Monthly income	100,000–150,000	29	9.8
Monthly income	150,000 and above	32	10.8

Note: five of the 300 returned questionnaires are marked as missing in the source frequency tables.

Reported investment engagement

The descriptive output indicates high self-reported investment engagement. The item “I regularly invest in financial instruments” has a reported mean of 4.79. Several other investment-behaviour items, including setting specific financial goals, confidence in one’s own investment decisions, risk-taking, reviewing and adjusting investments and reliance on professional financial advice, each have a reported mean of 4.58. These values suggest a sample that sees itself as active and confident in financial decision-making. Because the exact response anchors are not available in the study materials, the numerical means should be interpreted descriptively rather than translated into an assumed categorical label.

The concentration of identical means and standard deviations across several items also reinforces the need for caution. It may reflect genuinely similar response patterns, but together with the perfect correlation matrix it raises the possibility of duplicated coding or copied variables. For that reason, the descriptive statistics are reported without constructing a composite investment-behaviour index.

Table 2. Survey domains and indicators used in the analysis

Domain	Indicators available in the source output	Use in this article
Investment behaviour	Regular investment; financial goal setting; decision confidence; risk-taking; investment review; professional advice	Descriptive context; regular investment used as outcome in two complete models
Financial-literacy-related indicators	Active learning; perceived improvement through AI tools; long-term financial security; decision confidence; risk understanding	Risk understanding used as predictor; perfect inter-item correlations treated as a data-quality warning
AI-related engagement	AI makes complex concepts easier to understand; familiarity with AI in financial decision-making	Joint predictors of regular investment in the complete two-predictor model

Note: the available study materials do not specify the exact response anchors or a validated scale specification.

Financial risk understanding and regular investment

The most interpretable financial-literacy model tests whether understanding the risks associated with different types of investments predicts regular investment in financial instruments. The ANOVA table reports $F(1,293)=909.268$, $p<.001$. The regression sum of

squares is 37.471 and the total sum of squares is 49.546, corresponding to $R^2=.756$. Within this sample, the predictor is therefore strongly associated with regular investment activity.

This result is consistent with the general expectation that risk understanding is connected to investment participation. It does not establish that increasing risk knowledge by itself causes people to invest more regularly. The variables are measured in the same questionnaire at one point in time and may share response-style variance. It is also plausible that people who already invest regularly learn more about risk through experience. The result should therefore be read as a strong cross-sectional association that warrants replication with independently validated measures.

AI-related perceptions and regular investment

The second complete model tests two AI-related predictors jointly: the perception that AI makes complex financial concepts easier to understand and familiarity with using AI in financial decision-making. The model reports $F(2,292)=4406.231$, $p<.001$. The regression sum of squares is 47.957 and the total sum of squares is 49.546, giving $R^2=.968$. The two AI-related indicators are therefore jointly associated with regular investment activity in the observed sample.

The magnitude of this model fit is exceptionally high for behavioural survey research. It should not be interpreted as evidence that AI use explains nearly all investment behaviour in a population. A very high R^2 can result from strongly overlapping questionnaire items, common-method variance, restricted response patterns or coding duplication. The substantive conclusion is consequently modest: respondents who report greater AI familiarity and greater perceived usefulness of AI also report more regular investment, but the strength of the relationship requires verification from the raw data and preferably from an independent sample.

Results not used for inferential claims

Several additional ANOVA tables attempt to predict goal setting, investment confidence, risk-taking, portfolio review and reliance on professional advice from either risk understanding or AI-related predictors. In these outputs, the residual sum of squares is reported as zero and the F and significance columns are blank. Without an estimable error term and a reported significance test, these models cannot support a claim that the relevant predictor has a statistically significant effect and they are not used for inferential conclusions.

The same principle applies to the Pearson matrix of financial-literacy items. Because every displayed pair has $r=1.000$, the matrix cannot distinguish related but separate dimensions of literacy. It is therefore inappropriate to use it as confirmation that all dimensions mutually reinforce one another. Instead, it identifies a measurement problem that should be investigated before stronger construct-level conclusions are drawn.

Table 3. Inferential outputs retained for interpretation

Outcome	Predictor(s)	F test	p	R ²	Interpretation
Regular investment	Understanding risks of different investment types	F(1,293)=909.268	<.001	.756	Strong association; cross-sectional and non-causal
Regular investment	AI simplifies complex concepts + AI familiarity	F(2,292)=4406.231	<.001	.968	Strong association; exceptionally high fit requires raw-data verification
Other reported outcomes	Risk or AI predictors	F not reported	Not reported	Not estimable	Not used for significance claims

Note: R² values are reconstructed from the regression and total sums of squares shown in the source SPSS ANOVA tables.

Discussion

Financial literacy as an enabling resource

The clearest empirical relationship in the study is between risk understanding and regular investing. This is compatible with established research showing that financial knowledge is associated with market participation and investment decision-making (Lusardi and Mitchell 2014; Shroff 2024; van Rooij et al. 2011). In practical terms, understanding risk may reduce uncertainty about financial products and help individuals distinguish between acceptable volatility and unacceptable exposure. For salaried employees, such knowledge can support the conversion of regular income into more deliberate saving and investment routines.

The finding should not be reduced to a message that “more literacy always means more investing”. Financial literacy can also lead individuals to avoid unsuitable products, delay a decision until information improves or choose lower-risk instruments. The socially relevant outcome is therefore not trading frequency but the capacity to make decisions that are consistent

with one's objectives and constraints. This distinction is particularly important when financial applications are designed to encourage frequent engagement.

AI as a complementary rather than substitutive resource

The AI-related model suggests that familiarity with AI and the perception that AI helps simplify complex concepts are associated with regular investment activity. This aligns with technology acceptance research in which perceived usefulness is central to adoption (Davis 1989) and with studies showing that attitudes, trust, privacy and user-interface characteristics influence the acceptance of automated financial advice (Belanche et al. 2019; Hildebrand and Bergner 2021; Lourenço et al. 2020; Seiler and Fanenbruck 2021). The contribution of the present study is to place this relationship beside financial literacy rather than treating AI as a stand-alone technological determinant.

This complementary interpretation is more defensible than the idea that AI replaces financial capability. Automated systems can organise information and reduce cognitive effort, but investors still need a basis for evaluating recommendations. Choo et al. (2023) show that literacy and overconfidence are connected to robo-advisor adoption, which illustrates why adoption alone cannot be equated with good judgement. Similarly, Zhang et al. (2021) show that perceptions of expertise and trust differ between human and automated advisors. Financial literacy can therefore function as a critical layer through which AI outputs are interpreted rather than as a skill made obsolete by automation.

Social distribution of digital financial capability

The demographic composition of the sample deserves substantive attention. Nearly four-fifths of valid respondents are men and private-sector employees, while more than two-thirds are aged 25–34 and hold undergraduate degrees. The dominant income band is also relatively concentrated. These characteristics indicate that the study is observing a specific segment of salaried workers rather than an evenly distributed cross-section. Financial and digital capabilities are socially patterned, and a model estimated on a digitally exposed, well-educated group may not transfer to older workers, lower-income employees or people with limited access to digital services.

This point links the study to a broader social-science concern: technological access does not automatically produce equal capability. Digital finance can lower transaction costs while simultaneously creating new demands for knowledge, privacy awareness and algorithmic judgement. Ravikumar et al. (2022) treat digital financial literacy as a multidimensional competence for exactly this reason. In policy terms, interventions that simply introduce AI-enabled tools may widen rather than narrow capability gaps if users differ in their ability to evaluate the tools.

Implications for employers, financial institutions and policy

For employers, workplace financial education could be expanded beyond conventional topics such as budgeting and retirement planning to include AI literacy: how automated recommendations are produced, what data they use, what their limitations are and when human advice is appropriate. The goal should be informed use rather than promotional adoption. Employees should be able to recognise that a personalised interface can still rely on assumptions that may not match their circumstances.

For financial institutions, the findings support transparent interface design and educational scaffolding. If users value AI because it makes complex concepts easier to understand, then explanations, risk visualisations and clear statements of uncertainty may be as important as predictive sophistication. Trust should be earned through understandable processes and accountable advice, not through the appearance of certainty. Prior work on robo-advice similarly shows that trust and perceived expertise shape acceptance (Hildebrand and Bergner 2021; Lourenço et al. 2020).

For policy, the study suggests integrating financial literacy and digital-finance literacy rather than treating them as separate programmes. Education about diversification, risk and long-term goals should be paired with awareness of data privacy, automated decision support and the possibility of algorithmic error. Such integration is particularly relevant in markets where retail investment is increasingly app-based and where salaried employees are encouraged to take greater responsibility for long-term financial security.

Methodological implication: measurement matters as much as modelling

A further contribution of the study is methodological. The statistical outputs include very large F statistics, perfect correlations and zero-residual models. These features can easily produce an impression of overwhelming evidence. Yet statistical strength cannot compensate for a questionable measurement structure. Perfect inter-item correlations may indicate that conceptually different questions are not functioning as distinct variables, while zero residual variance prevents ordinary inferential interpretation. Social-science research on AI is especially vulnerable to this problem because new constructs are often measured quickly as technologies evolve. Stronger research requires validated items, transparent coding and full reporting of model diagnostics.

Limitations and future research

Several limitations constrain the conclusions. First, the survey uses a non-probability online sample with strong demographic concentration. The results cannot be generalised to all salaried employees. A future study should use a clearly defined sampling frame and deliberately recruit across age, gender, income, education and employment sectors.

Second, the study is cross-sectional and self-reported. Regular investing, confidence and AI engagement are reported by the same respondents at the same time, which can inflate relationships through common-method variance. Future work should combine surveys with behavioural indicators such as verified platform use, portfolio diversification, transaction frequency or longitudinal changes in investment allocation.

Third, the available study documentation does not specify scale anchors, item development, reliability or construct validation in sufficient detail. The perfect correlations among financial-literacy items and repeated zero-residual regression tables require a raw-data audit before stronger claims are made. At minimum, future analysis should check duplicate variables, frequency distributions, coding direction, missing-value treatment and the correlation matrix. A redesigned study should then test measurement quality through reliability analysis and confirmatory factor analysis before estimating structural relationships.

Fourth, the AI construct is narrow. Familiarity and perceived conceptual assistance do not capture frequency of use, type of AI system, trust, privacy concern, explainability, degree of

automation or whether the tool actually influences a transaction. These dimensions matter because robo-advisory research shows that acceptance is shaped by usefulness, trust, privacy and interface characteristics (Belanche et al. 2019; Hildebrand and Bergner 2021; Seiler and Fanenbruck 2021). Future questionnaires should distinguish informational AI, recommendation AI and fully automated portfolio management.

Fifth, the study cannot establish whether AI engagement improves financial outcomes. A person may invest more regularly without achieving a more diversified or suitable portfolio. Future research should therefore distinguish participation from decision quality and should test whether financial literacy moderates the relationship between AI use and objective investment outcomes. An experimental design could compare decisions made with no AI support, explainable AI support and opaque AI support across participants with different levels of objective financial literacy.

Conclusion

This study revisits survey evidence on financial literacy, AI-related financial tools and the investment behaviour of salaried employees. Its most reliable empirical results show strong cross-sectional associations between risk understanding and regular investment activity, and between two AI-related perceptions and regular investment activity. These findings fit a socio-technical interpretation in which investment behaviour is shaped by both human capability and engagement with digital decision-support tools.

The contribution is not that AI should replace financial education. On the contrary, the evidence and the wider literature suggest that financial literacy remains important precisely because automated finance asks individuals to assess recommendations, risks and institutional trust. AI can make information easier to process, but users still need the capacity to judge whether an output is appropriate for their goals. In this sense, financial literacy and AI engagement are better understood as complementary resources.

At the same time, perfect correlations among financial-literacy items and missing inferential statistics in several ANOVA tables prevent a blanket conclusion that every hypothesised relationship is significant. A raw-data audit and a new validation study are needed before stronger construct-level claims can be made. This caution does not weaken the social relevance

of the topic; it clarifies the conditions under which evidence about AI and financial behaviour should be trusted.

For research and practice, the implication is straightforward. Digital investment participation should be supported by financial knowledge, AI literacy and transparent systems. Future studies that combine validated measures, more diverse samples and behavioural outcomes can determine when AI genuinely improves investment decision quality and for whom. Such work will be essential as responsibility for personal financial security increasingly moves into digitally mediated environments.

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