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Artificial Intelligence Use and Financial Behaviour among Students: Evidence from an Empirical Survey

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ABSTRACT

Artificial Intelligence (AI) tools have become essential components of students' academic and independent learning activities, particularly in the acquisition of financial concepts. Given that AI-generated financial information may be incomplete, inaccurate, or lack sufficient context, responsible engagement with these tools is especially critical in this field. This study examines students' awareness and use of AI tools and analyses the associations of perceived AI value, AI trust and perceived reliability, verification behaviour, AI usage frequency, and finance-related AI use with self-reported financial behavioral outcomes. An empirical survey of 179 higher-education students was conducted, with 172 complete cases used for construct-level and regression analyses. Descriptive statistics, reliability and item-level measurement diagnostics, correlation analysis, common-method-variance screening, and multiple regression with diagnostic and robustness checks were employed. The regression model was statistically significant ($R^2 = 0.548$, adjusted $R^2 = 0.534$). Perceived AI value ($\beta = 0.240$, $p < 0.001$), AI trust and perceived reliability ($\beta = 0.359$, $p < 0.001$), verification behaviour ($\beta = 0.184$, $p = 0.003$), and AI usage frequency ($\beta = 0.240$, $p < 0.001$) were positively associated with self-reported financial behavioral outcomes, whereas finance-related AI use was not statistically significant after the other predictors were included ($\beta = 0.114$, $p = 0.085$). These findings suggest that the quality and criticality of students' engagement with AI-generated financial information may be more relevant than the mere use of AI for financial topics. Because the study is cross-sectional and self-reported, the findings are interpreted as associations rather than causal effects. AI should therefore be treated as a guided learning support tool rather than a replacement for teachers, verified sources, or professional financial advice.

Introduction

Background of the Study

The proliferation of digital platforms and Artificial Intelligence (AI) tools has fundamentally transformed students' learning environments. Learners now supplement traditional classroom lectures, textbooks, and teacher explanations with AI-based tools to simplify complex subjects, generate examples, complete assignments, resolve doubts, and support self-directed learning. Recent discourse on large language models in education indicates that these tools can facilitate explanation, feedback, content creation, and independent learning. However, their effective use requires thoughtful judgment and appropriate guidance (Kasneci et al., 2023).

Concurrently, concerns remain regarding accuracy, privacy, transparency, bias, and the necessity for human oversight in the integration of AI within educational contexts (Yan et al., 2024). Collectively, these developments suggest that generative AI represents a transformative educational tool, although its advantages must be balanced against potential pedagogical and institutional challenges

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(Lim et al., 2023). This transformation is particularly significant for financial literacy. Financial literacy extends beyond formal education, influencing daily financial decisions such as saving, spending, borrowing, investing, risk management, and future planning. Lusardi and Mitchell (2014) identify financial knowledge as a critical form of human capital that shapes both economic choices and personal well-being. The Organisation for Economic Co-operation and Development (OECD, 2020) defines financial literacy as a combination of awareness, knowledge, skills, attitudes, and behaviors that enable individuals to make informed financial decisions and enhance well-being. For students, financial literacy is especially important as habits, attitudes, and financial socialization are formed during the transition to adulthood and higher education (Shim et al., 2009). Many students manage pocket money, digital payments, online shopping, education expenses, banking, and, in some cases, borrowing or investments.

The OECD's PISA 2022 financial literacy report also emphasizes the need to prepare youth for financial decision-making in a digital world (OECD, 2024). Nevertheless, concepts such as budgeting, saving, interest, inflation, risk, return, borrowing costs, and investment planning can be challenging, particularly for those without a background in finance. AI tools can provide valuable support in this context by explaining financial topics in accessible terms, offering examples, answering repeated questions, and enabling students to learn at their own pace. For individuals hesitant to ask basic questions in class, AI offers a less intimidating avenue for exploring financial subjects. However, reliance on AI for financial learning is sensitive, as inaccurate or unverified information may adversely affect students' real-world financial understanding and behavior. For this reason, UNESCO (2023) underscores the importance of responsible and human-centered use of generative AI in education, with careful attention to regulation, privacy, institutional readiness, and sound educational practices.

Research Problem

The increasing use of artificial intelligence (AI) tools by students presents both opportunities and risks. The central issue extends beyond mere access to AI tools, focusing instead on whether various forms of AI engagement are associated with students' self-reported financial behavioral outcomes. Facilitating financial learning through AI may be achieved by clarifying complex concepts and promoting autonomous learning.

However, using AI-generated financial information as definitive advice without verification can lead to inaccurate or incomplete information, over-reliance, and lack of adequate access to appropriate human support (Consumer Financial Protection Bureau, 2023; Yan et al., 2024).Thus, the main issue explored in this research is not only whether students employ AI for financial learning but also how various aspects of AI engagement are associated with students' self-reported financial behavioral outcomes. It is crucial to distinguish perceived value and frequency of use from students' trust in the reliability of AI-generated information, and from the separate behavior of verifying that information before relying on it.

Research Gap

Research on financial literacy has mainly focused on financial knowledge, education, attitudes, and behavior, while studies on AI in education have concentrated on application areas, learning support, and practical and ethical challenges (Hastings et al., 2013; Zawacki-Richter et al., 2019; Yan et al., 2024). These two bodies of literature have mostly developed in isolation. The literature reviewed for this study revealed relatively little empirical evidence on the link between students' use of AI for finance-related learning and their self-reported financial behavior.While trust and appropriate reliance have been explored in human–AI research (Glikson & Woolley, 2020; Lee & See, 2004), verification behavior in the specific context of AI-supported financial learning is still underexplored. This study addresses the gap by distinguishing AI trust and perceived reliability from verification behavior and by examining both alongside perceived AI value, AI usage frequency, finance-related AI use, and students' self-reported financial behavioral outcomes.

Research Questions

- The research questions that drive this study are
- What is the level of awareness and use of AI tools among students?
- How are perceived AI value, AI trust and perceived reliability, verification behavior, AI usage frequency, and finance-related AI use associated with students' self-reported financial behavioral outcomes?
- What concerns do students report while using AI tools for financial learning?

Research Objectives

- The aims of the study are
- To examine students' awareness and usage of AI tools.
- To analyse the extent to which students use AI tools for finance-related learning.
- To assess students' perceived AI value, AI trust and perceived reliability, and verification behaviour regarding AI-generated financial information.
- To examine the associations between AI-related factors and students' self-reported financial behavioral outcomes.
- To identify major concerns associated with the use of AI tools for financial learning.

Contribution of the Study

The study contributes to the literature in three ways.

First, it provides empirical evidence on the use of AI tools among higher-education students in the context of financial learning. Second, it distinguishes perceived technology value and usage from two conceptually different dimensions of responsible engagement: AI trust and perceived reliability, and verification behaviour. Third, it links these dimensions with self-reported financial behavioral outcomes while explicitly recognising the limits of cross-sectional, self-report evidence. The framework therefore shifts the emphasis from AI adoption alone to the quality and criticality of students' engagement with AI-generated financial information.

Structure of the Paper

The remaining paper is organised as follows. Section 2 reviews the relevant literature on financial literacy, AI in education, and responsible AI use. Section 3 presents the conceptual framework. Section 4 explains the research methodology. Section 5 presents the results and analysis. Section 6 discusses the findings. Section 7 outlines the study's implications. Section 8 presents limitations and future research directions, and Section 9 concludes the paper.

Literature Review

Financial literacy encompasses more than the possession of financial knowledge; it also requires the capacity to understand financial concepts and apply them in practical decision-making. Huston (2010) asserts that financial literacy involves both knowledge and the ability to utilize that knowledge effectively. Atkinson and Messy (2012) similarly define financial literacy as a combination of financial knowledge, behavior, and attitude. This comprehensive perspective is essential, as financial literacy is demonstrated not only through comprehension of financial terminology but also through everyday practices such as saving, budgeting, borrowing, planning, and making informed financial decisions. The manner in which financial literacy is conceptualized and measured is particularly significant when examining its association with financial outcomes. Literature reviews indicate that conclusions regarding financial literacy, financial education, and economic outcomes are highly contingent upon the definitions and measurement approaches used for financial knowledge, behavior, and related constructs (Hastings et al., 2013). Financial behavior is thus a central element of financial literacy. Xiao (2008) defines financial behavior broadly as actions related to money management, including cash, credit, savings, and investment-related activities. Among students, these behaviors may be straightforward yet meaningful, such as managing expenditures, saving consistently, comparing alternatives prior to making purchases, and using digital financial services judiciously. Students constitute a critical population for financial literacy research, as they are in a formative stage where financial habits and attitudes are still developing. Shim et al. (2009) show that young adults' financial well-being is shaped by early financial socialisation, financial learning, attitudes, and behaviours. A growing body of evidence has examined the behavioral effects of financial education. Earlier meta-analyses reported that financial education produced relatively small effects on subsequent financial behavior and suggested that these effects may diminish over time (Fernandes et al., 2014). In contrast, a more recent meta-analysis of 76 randomized experiments identified positive causal effects on both financial knowledge and downstream financial behavior, with no strong evidence of rapid decay, although the long-term effects remain uncertain (Kaiser et al., 2022). Collectively, these findings suggest that the magnitude and durability of financial education's effects depend on factors such as program design, study methodology, timing, and contextual variables. This underscores the need to examine emerging learning tools available to students and the specific circumstances in which these tools may influence financial behavior. The expansion of digital learning has significantly altered how students access financial information. Students increasingly utilize online platforms, videos, mobile applications, and other digital resources to acquire financial knowledge. According to the OECD (2021), digital delivery can broaden access to financial education and facilitate more flexible, personalized learning experiences. However, digital access alone does not ensure improved financial understanding. The OECD (2018) notes that digitalization introduces both opportunities and risks, highlighting the necessity of digital financial literacy. Although students are often adept at using digital tools, they must also develop the capacity to critically evaluate financial information. The emergence of Artificial Intelligence (AI) tools has further transformed digital learning. AI can support students by simplifying complex material, generating illustrative examples, responding to repeated queries, and enabling self-paced learning. Zawacki-Richter et al. (2019), in a systematic review of AI applications in higher education, identify four major application areas: profiling and prediction, assessment and evaluation, adaptive systems and personalisation, and intelligent tutoring systems. Holmes et al. (2019) discuss both the opportunities AI offers for teaching and learning and the wider implications of its adoption for curricula, educators, and educational systems.

The Consumer Financial Protection Bureau (2023) cautions that the use of chatbots in consumer finance introduces risks when these systems provide inaccurate or insufficient information. Although this warning targets financial institutions, it is equally pertinent for students utilizing AI tools in finance-related education. While AI can facilitate the explanation of financial topics, it should not be considered a substitute for professional financial advice. Consequently, trust and verification are essential in AI-supported financial learning. Students derive value from AI only when they critically evaluate the accuracy, relevance, and appropriateness of AI-generated responses. The High-Level Expert Group on Artificial Intelligence (2019) identifies human agency and oversight, technical robustness and safety, privacy and data governance, transparency, diversity and fairness, societal and environmental well-being, and accountability as fundamental requirements for trustworthy AI. The OECD (2019) similarly underscores the importance of responsible stewardship in the development of human-centered, trustworthy AI. Research demonstrates that human trust in AI is influenced by system characteristics such as transparency, reliability, capability, and representation (Glikson & Woolley, 2020). Responsible use requires appropriately calibrated reliance, rather than uncritical acceptance or complete rejection of automated support (Lee & See, 2004). In the context of financial literacy education, students should corroborate AI-generated responses with textbooks, official sources, educators, or qualified professionals as needed.

Theoretical Rationale and Hypothesis Development

The Technology Acceptance Model (TAM) offers a limited perspective for understanding why students' perceptions of usefulness and ease of use may relate to their engagement with AI tools (Davis, 1989). This study does not examine behavioral intention or the full causal structure of TAM, so it should not be seen as a validation or extension of the entire TAM framework. Rather, TAM informs the perceived-value component of a broader framework for AI-supported financial learning.

In financial learning, perceived usefulness alone is insufficient because a system may be convenient and valuable for explanation while still producing information that is incomplete, inaccurate, or unsuitable for a particular decision context. The TAM-informed perspective is therefore complemented by research on trust in automation and responsible AI use. Human–AI research emphasises appropriately calibrated reliance rather than either blind acceptance or blanket rejection (Lee & See, 2004), while trust in AI is shaped by perceived reliability, capability, and transparency (Glikson & Woolley, 2020). Guidance on responsible artificial intelligence highlights the significance of human oversight, transparency, privacy, and accountability (High-Level Expert Group on Artificial Intelligence, 2019; OECD, 2019; UNESCO, 2023). Perceived AI value refers to the extent to which students consider AI easy to use, useful, and supportive of comprehension and self-directed learning. Higher perceived learning value may encourage more active engagement with explanations and examples, which can contribute to improved financial learning outcomes. Based on these considerations, the study proposes:

- H1: Perceived AI value is positively associated with students' self-reported financial behavioral outcomes.
- Trust and verification are related to responsible reliance on AI, yet they represent distinct constructs. Trust and perceived reliability denote students' confidence in the trustworthiness, accuracy, and dependability of AI-generated financial information. Verification behaviour involves independently checking AI-generated information prior to acceptance or application. Differentiating these dimensions is crucial in finance, where both calibrated trust and critical evaluation are necessary. Accordingly, the study proposes:
- H2a: AI trust and perceived reliability are positively associated with students' self-reported financial behavioral outcomes.
- H2b: Verification behaviour is positively associated with students' self-reported financial behavioral outcomes.
- AI usage frequency denotes repeated exposure to AI-supported explanations and learning interactions. Increased engagement may offer more opportunities to encounter, clarify, and revisit financial concepts, although frequency alone does not ensure accuracy or effective application. Thus:
- H3: AI usage frequency is positively associated with students' self-reported financial behavioral outcomes.
- Finance-related AI use refers to domain-specific engagement with AI for financial concepts, budgeting and saving, investment-related inquiries, and related learning needs. Although domain-specific exposure may positively influence financial outcomes, the breadth of use does not necessarily indicate the quality of engagement. Accordingly:
- H4: Finance-related AI use is positively associated with students' self-reported financial behavioral outcomes.

Conceptual Framework

The conceptual framework outlines how five AI-related factors are hypothesized to relate to students' self-reported financial behavioral outcomes. Importantly, the framework does not assume that AI use directly causes behavioral change. Instead, it distinguishes technology value and frequency of use from domain-specific use and from the quality of students' reliance on AI-generated information. The model includes five independent variables: perceived AI value, AI trust and perceived reliability, verification behaviour, AI usage frequency, and finance-related AI use. Perceived AI value encompasses students' assessments of the usefulness and ease of use of AI tools, as well as their perceived support for understanding, interest, confidence, and self-directed

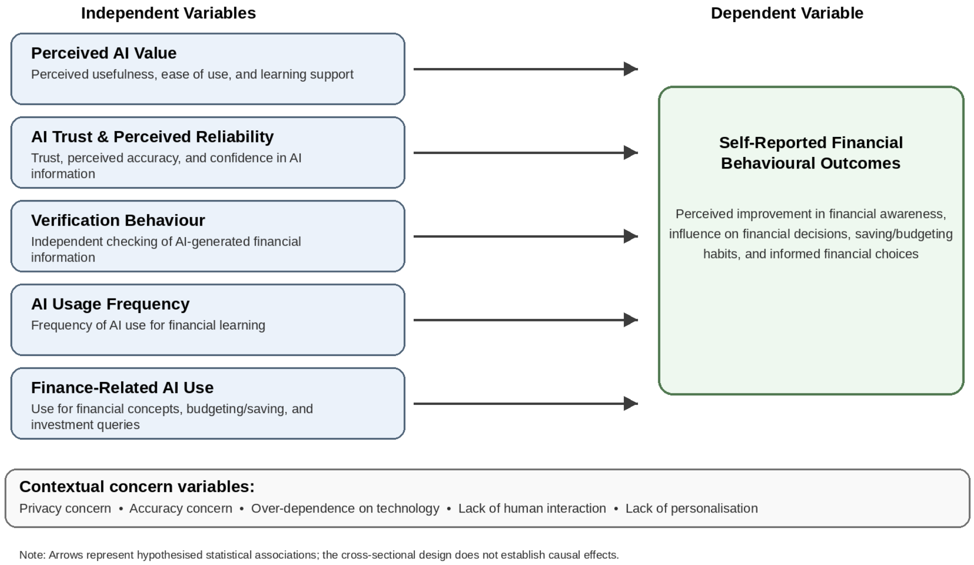

Figure 1: Conceptual Framework of AI Engagement and Self-Reported Financial Behavioral Outcomes

learning. AI trust and perceived reliability denote trust in AI-generated financial information, perceived accuracy, and confidence in relying on AI outputs. Verification behaviour is treated as a distinct construct, referring to whether students independently verify AI-generated information prior to acceptance or application. AI usage frequency quantifies how often students utilize AI tools for financial learning. Although repeated use may increase exposure to explanations and examples, frequent usage alone does not ensure effective learning or responsible application. Finance-related AI use reflects the breadth of domain-specific engagement, including financial learning, conceptual understanding, budgeting or saving advice, and investment-related inquiries. The dependent variable comprises self-reported financial behavioral outcomes, such as perceived improvements in financial awareness, influence on financial decisions, saving and budgeting habits, and support for informed financial choices. These outcomes are based on subjective self-reports rather than objective financial literacy scores or observed behaviours. The framework also considers contextual factors such as privacy, accuracy, over-reliance on technology, limited human interaction, and lack of personalization. These factors are described qualitatively and are not included as direct predictors in the primary model. Overall, the framework investigates whether various forms of AI engagement are statistically associated with self-reported financial behavioral outcomes. The distinction between AI trust and perceived reliability and verification behaviour is emphasized, as responsible use necessitates both confidence in system reliability and independent verification of information prior to reliance.

Research Methodology

Research Design

The study follows an empirical, survey-based research design. A quantitative approach was used to examine students' awareness and use of AI tools and the statistical

Table 1: Demographic Profile of Respondents

Demographic Variable	*Category*	*Frequency*	*Percentage*
Age	Below 20	11	6.15
	20–24	55	30.73
	25–29	82	45.81
	30 and above	31	17.32
Gender	Male	83	46.37
	Female	96	53.63
Education	Undergraduate	49	27.37
	Postgraduate	94	52.51
	Doctorate	36	20.11
Field of Study	Commerce/ Management	116	64.80
	Economics	5	2.79
	Science	6	3.35
	Engineering/ Technology	3	1.68
	Arts/Humanities	32	17.88
	Other	17	9.50

Table 2: Awareness and Usage of AI Tools

Variable	*Response*	*Frequency*	*Percentage*
Awareness of AI tools	Yes	172	96.1
	No	7	3.9
Used AI tools for learning	Yes	166	92.7
	No	13	7.3
Used AI tools for finance-related learning	Yes	124	69.3
	No	48	26.8
	No response	7	3.9

Table 4: Purposes of AI Use

Purpose of AI Use	*Frequency*	*Percentage*
General knowledge	117	65.4
Academic assignments	109	60.9
Understanding financial concepts	84	46.9
Investment-related queries	46	25.7
Budgeting and saving advice	43	24.0

associations between AI-related factors and self-reported financial behavioral outcomes. The study is cross-sectional, as data were collected from respondents at a single point in time. Therefore, the results are interpreted as associations rather than evidence of causal effects.

Population, Sampling and Sample Size

The study targeted higher-education students as the population of interest. Students were selected because they are active users of digital learning tools and are at a stage where financial habits, attitudes, and decision-making patterns are still developing. The sampling unit was the individual student. A convenience sampling method was used, distributing the questionnaire via academic and online networks. As a result, this non-probability design does not yield a representative sample of all higher-education students, which limits the generalizability of the findings; thus, results are interpreted as evidence from the surveyed sample rather than as population estimates. The final dataset included 179 responses. For construct-level, correlation, common-method, and multiple-regression analyses, 172 complete cases were available. A power analysis using G*Power 3.1 for multiple linear regression with five predictors (Faul et al., 2009) indicated a minimum sample size of 138 (with $\alpha = .05$, statistical power = .95, and a medium effect size of $f^2 = .15$). The 172 complete cases used in the regression analysis therefore exceeded this benchmark.

Table 3: Frequency of AI Use for Financial Learning

Frequency of Use	*Frequency*	*Percentage*
Very often	49	27.4
Occasionally	59	33.0
Rarely	34	19.0
Never	30	16.8
No response	7	3.9

Data Collection

Primary data were collected using a structured online questionnaire distributed via Google Forms. The questionnaire collected data on students' demographic characteristics, awareness and utilization of AI tools, application of AI in finance-related learning, frequency of AI usage, perceived value of AI, trust and verification practices, financial behaviors, and concerns regarding AI use. Participation was voluntary, and responses were exclusively used for academic research purposes. Prior to analysis, all responses were assessed for completeness and relevance.

Measurement of Variables

The questionnaire comprised categorical, binary, frequency, and five-point Likert-scale items. Awareness of artificial intelligence (AI), actual AI use, and AI use for finance-related purposes were assessed using categorical responses. AI usage frequency was coded on a scale from 1 (Never) to 4 (Very often). Items related to purpose and concerns were coded as binary variables, with 1 indicating selection of an option and 0 indicating non-selection.

The primary model incorporated five independent variables: perceived AI value, AI trust and perceived reliability, verification behaviour, AI usage frequency, and finance-related AI use. Perceived AI value was measured using six items: ease of use, usefulness of information, support in understanding concepts, interest in learning, confidence, and self-learning. AI trust and perceived reliability were assessed with three items: trust in AI information, perceived accuracy, and confidence in relying on AI. Verification behaviour was measured separately by asking whether respondents verify information obtained from AI tools. Finance-related AI use was calculated as an index based on reported use of AI for financial learning and for activities related to financial concepts, budgeting or saving, and investment. The dependent variable, self-reported financial behavioral outcomes, was constructed from four items: perceived improvement in financial

Table 5: Descriptive Statistics of Model Variables

Variable	*N*	*Mean*	*Standard Deviation*	*Interpretation*
Perceived AI Value	172	3.77	0.85	Agreement
AI Trust and Perceived Reliability	172	3.09	0.77	Moderate/Neutral
Verification Behaviour	172	3.86	0.99	Agreement
Self-Reported Financial Behavioral Outcomes	172	3.46	0.72	Agreement
AI Usage Frequency	172	2.74	1.06	Between rarely and occasionally
Finance-Related AI Use Index	172	0.43	0.34	Moderate use

Table 6: Reliability Analysis of Study Measures

Measure	*Number of Items*	*Cronbach's Alpha*	*Interpretation*
Perceived AI Value	6	0.916	Strong reliability
AI Trust and Perceived Reliability	3	0.819	Good reliability
Verification Behaviour	1	—	Single-item observed indicator
Self-Reported Financial Behavioral Outcomes	4	0.839	Good reliability

awareness, influence on financial decisions, improvement in saving and budgeting habits, and support for informed financial choices.

Measurement Quality and Data Analysis

The quality of the measurement was assessed prior to the main analysis. Perceived AI value and the self-reported financial behavioral outcomes were kept as multi-item composite measures. Trust, perceived accuracy, verification, and confidence were first treated as four separate items; however, since verification involves a checking behaviour rather than a perception of the system's reliability, item-level diagnostics were carried out to decide whether it should be analysed on its own. The analysis therefore separates the three-item composite consisting of AI trust and perceived reliability from the single-item verification behaviour indicator. Cronbach's alpha was used to examine the internal consistency of the multi-item measures.

The data were analyzed using spreadsheet and statistical software. Descriptive statistics were used to present respondents' profiles, AI awareness, usage patterns, purposes, and concerns. Reliability and item-level diagnostics were used to assess measurement quality. Pearson correlation analysis examined bivariate associations. Multiple linear regression examined the unique associations of the five AI-related predictors with self-reported financial behavioral outcomes. Common-method variance was screened using Harman's single-factor test. Regression diagnostics included variance inflation factors and tolerance, residual normality, heteroscedasticity, functional-form specification, Durbin–Watson, and influence diagnostics. Ninety-five per cent confidence intervals and partial R^2 values were used to improve effect-size reporting. HC3 heteroscedasticity-consistent standard errors and a sensitivity model including age, gender, and education level were examined as robustness checks.

Results and Analysis

This section presents the study's empirical findings. The total sample consisted of 179 respondents. For construct-level, correlation, common-method, and regression analyses, 172 complete cases were used because seven respondents had incomplete AI-related Likert-scale and frequency responses. The analysis includes respondent profile, AI awareness and use, descriptive statistics, measurement assessment, common-method-variance screening, correlation analysis, regression diagnostics and hypothesis testing, robustness checks, and concerns related to AI use.

Respondents' Profile

Table 1 shows the demographic profile of the respondents. The sample consists of students representing a range of age groups, gender categories, education levels, and fields of study.

The sample predominantly consists of postgraduate students and individuals from commerce and management disciplines. This composition is pertinent to the study, given its focus on financial literacy and financial behaviour; however, the disciplinary concentration should be taken

Table 7: Correlation Matrix

Variable	*Perceived AI Value*	*AI Trust & Reliability*	*Verification Behaviour*	*AI Usage Frequency*	*Finance-Related AI Use*	*Self-Reported Financial Behavioral Outcomes*
Perceived AI Value	1.000	0.327	0.512	0.142	0.112	0.498
AI Trust & Reliability	0.327	1.000	0.247	0.224	0.125	0.551
Verification Behaviour	0.512	0.247	1.000	0.150	0.140	0.447
AI Usage Frequency	0.142	0.224	0.150	1.000	0.605	0.451
Finance-Related AI Use	0.112	0.125	0.140	0.605	1.000	0.357
Self-Reported Financial Behavioral Outcomes	0.498	0.551	0.447	0.451	0.357	1.000

Note: Correlations between each AI-related predictor and self-reported financial behavioral outcomes are statistically significant at $p < 0.001$.

Table 8: Regression Model Summary

Model	*R*	*R^2*	*Adjusted R^2*	*F-value*	*df*	*p-value*
Regression Model	0.740	0.548	0.534	40.244	5, 166	< 0.001

into account when interpreting the results.

Awareness, Usage and Purpose of AI Tools

The results show a high level of AI awareness and usage among students. As shown in Table 2, 96.1% of respondents were aware of AI tools, and 92.7% had used them for learning. Further, 69.3% reported using AI tools for finance-related learning.

The frequency of AI use for financial learning is presented in Table 3. Around 60.4% of respondents used AI either occasionally or very often for finance-related learning.

Students used AI tools for several purposes. Since this was a multiple-response item, respondents could select more than one option. General knowledge and academic assignments were the most common purposes, followed by understanding financial concepts.

The results indicate that AI tools were utilised more frequently for general knowledge acquisition and academic assignments than for specific budgeting, saving, or investment-related inquiries. Nonetheless, a considerable proportion of respondents reported using AI to enhance their understanding of financial concepts.

Descriptive Statistics and Measurement Assessment

Table 5 presents descriptive statistics for the variables used in the model. Perceived AI value, AI trust and perceived reliability, and self-reported financial behavioral outcomes were calculated as composite mean scores. Verification behaviour was represented by its single Likert item, AI usage frequency used the four-point frequency code, and finance-related AI use was measured as an index of selected finance-related uses.

Perceived AI value had a mean of 3.77, indicating generally favourable perceptions of the learning value of AI. AI trust and perceived reliability had a lower mean of 3.09, while verification behaviour had a comparatively higher mean of 3.86. The self-reported financial behavioral outcome score had a mean of 3.46. These descriptive differences reinforce the value of distinguishing perceived trust/reliability from the separate act of verification.

Reliability and item-level diagnostics were then examined. The four-item trust/reliability grouping, which included verification, yielded $\alpha = 0.724$. However, the verification item showed a corrected item–total correlation of 0.247, compared with 0.597–0.641 for the other three items. Sampling adequacy for exploratory item assessment was acceptable (KMO = 0.732), and Bartlett's test of sphericity was significant, $\chi^2(6) = 198.76$, $p < 0.001$. The verification item also showed a clearly weaker loading in a one-component check than the three trust/reliability items. Removing verification increased the reliability of the remaining three-item AI trust and perceived reliability measure to $\alpha = 0.819$. Verification was therefore analysed separately as a single-item observed indicator.

The retained multi-item constructs show good to strong internal consistency. Perceived AI value had $\alpha = 0.916$, AI trust and perceived reliability had $\alpha = 0.819$, and self-reported financial behavioral outcomes had $\alpha = 0.839$. Cronbach's alpha is not applicable to verification behaviour because it is represented by a single observed item. The separation of verification from trust/reliability addresses the conceptual distinction between perceived system reliability and independent checking behaviour.

Common Method Variance Assessment

Since both predictor and outcome measures were collected via the same self-report questionnaire, common-method

Table 9: Regression Coefficients, Confidence Intervals, and Effect Sizes

Predictor	*B*	*SE*	*β*	*t*	*p*	*95% CI for B*	*Partial R^2*
Intercept	0.561	0.217	—	2.581	0.011	[0.132, 0.990]	—
Perceived AI Value	0.204	0.053	0.240	3.834	< 0.001	[0.099, 0.309]	0.081
AI Trust & Perceived Reliability	0.340	0.053	0.359	6.355	< 0.001	[0.234, 0.445]	0.196
Verification Behaviour	0.135	0.045	0.184	2.998	0.003	[0.046, 0.224]	0.051
AI Usage Frequency	0.164	0.046	0.240	3.590	< 0.001	[0.074, 0.255]	0.072
Finance-Related AI Use	0.241	0.139	0.114	1.731	0.085	[-0.034, 0.516]	0.018

Table 10: Hypothesis Testing Results

Hypothesis	*Statement*	*Result*
H1	Perceived AI value is positively associated with students' self-reported financial behavioral outcomes.	Supported
H2a	AI trust and perceived reliability are positively associated with students' self-reported financial behavioral outcomes.	Supported
H2b	Verification behaviour is positively associated with students' self-reported financial behavioral outcomes.	Supported
H3	AI usage frequency is positively associated with students' self-reported financial behavioral outcomes.	Supported
H4	Finance-related AI use is positively associated with students' self-reported financial behavioral outcomes.	Not supported

variance was assessed using Harman's single-factor test. An unrotated principal-components analysis of the 14 Likert-scale items produced three components with eigenvalues above 1 (6.339, 2.201, and 1.155). The first component accounted for 45.28% of the total variance, so it did not explain the majority of the covariance among the measures. This result does not indicate a dominant single common-method factor. However, Harman's test is only a diagnostic tool, and common-method variance cannot be completely ruled out, as all variables were collected from the same respondents at the same time.

Correlation Analysis

Pearson correlation analysis was used to assess the direction and strength of associations among the study variables. All five AI-related variables showed statistically significant positive bivariate associations with self-reported financial behavioral outcomes. The results are detailed in Table 7.

The strongest bivariate association with self-reported financial behavioral outcomes was observed for AI trust and perceived reliability ($r = 0.551$), followed by perceived AI value ($r = 0.498$), AI usage frequency ($r = 0.451$), verification behaviour ($r = 0.447$), and finance-related AI use ($r = 0.357$). Finance-related AI use was strongly associated with AI usage frequency ($r = 0.605$), indicating substantial shared variance between general frequency and domain-specific use. Because bivariate correlations do not show each predictor's unique contribution, multiple regression analysis was conducted.

Regression Analysis and Hypothesis Testing

Multiple linear regression was conducted to examine the unique associations of perceived AI value, AI trust and perceived reliability, verification behaviour, AI usage frequency, and finance-related AI use with students' self-reported financial behavioral outcomes. The analysis used 172 complete cases and a 5% significance level.

The regression model was statistically significant, $F(5, 166) = 40.244$, $p < 0.001$. The model explained 54.8% of the variance in self-reported financial behavioral outcomes ($R^2 = 0.548$; adjusted $R^2 = 0.534$), representing a large overall effect (Cohen's $f^2 = 1.21$). The five-predictor specification provided substantial explanatory power while treating trust/reliability and verification behaviour as distinct variables.

Table 11: Concerns Related to AI Use

Concern	*Frequency*	*Percentage*
Data privacy concerns	103	57.5
Over-dependence on technology	79	44.1
Lack of human interaction	65	36.3
Inaccurate information	63	35.2
Lack of personalisation	54	30.2
No concerns	18	10.1

Regression diagnostics indicated no serious violations. VIF values ranged from 1.17 to 1.64 and tolerance values from 0.61 to 0.85, showing no multicollinearity concerns. Residuals were approximately normal (Jarque–Bera p = 0.915). The Breusch–Pagan test showed no significant heteroscedasticity at the 5% level (p = 0.062), and the Ramsey RESET test indicated no functional-form misspecification (p = 0.728). Durbin–Watson was 2.228. The maximum Cook's distance was 0.093; one externally studentised residual exceeded |3|, but removing that observation did not change the substantive conclusions. HC3 robust standard errors also produced the same hypothesis decisions.

The regression results show that AI trust and perceived reliability had the largest standardised coefficient (β = 0.359, p < 0.001), followed by perceived AI value (β = 0.240, p < 0.001), AI usage frequency (β = 0.240, p < 0.001), and verification behaviour (β = 0.184, p = 0.003). Finance-related AI use remained positive but was not statistically significant after the other predictors were included (β = 0.114, p = 0.085; 95% CI for B = [-0.034, 0.516]). Thus, domain-specific AI use did not demonstrate a statistically significant unique association with the outcome in the multivariable model.

As an additional sensitivity check, age, gender, and education level were added to the main model. These controls did not significantly improve the model fit (ΔR^2 = 0.008; F-change(4, 162) = 0.695, p = 0.596), and the main conclusions for the five AI-related predictors remained unchanged. While this robustness check does not make the convenience sample representative, it suggests that the primary results were not materially affected by these demographic controls.Based on the regression results, the hypotheses were evaluated as shown in Table 10.

H1, H2a, H2b, and H3 were supported because perceived AI value, AI trust and perceived reliability, verification behaviour, and AI usage frequency each showed statistically significant positive associations with self-reported financial behavioral outcomes. H4 was not supported because finance-related AI use was not statistically significant at the 5% level after the other predictors were included.

Concerns Related to AI Use

The study also examined students' concerns regarding the use of AI tools for financial learning. Since this was a multiple-response item, respondents could select more than one concern.

Data privacy was the most commonly mentioned concern, followed by over-reliance on technology, lack of human interaction, inaccurate information, and lack of personalisation. These results show that students recognize both the advantages and risks of using AI tools. Therefore, AI-supported financial learning should incorporate verification practices, privacy awareness, and responsible usage.

Summary of Results

Overall, the results indicate high awareness and usage of AI tools among surveyed students, with 69.3% reporting some use of AI for finance-related learning. In the regression model, perceived AI value, AI trust and perceived reliability, verification behavior, and AI usage frequency were all significant positive predictors of self-reported financial behavioral outcomes. While finance-related AI use showed a positive bivariate correlation with the outcome, it was not statistically significant once the other predictors were included. AI trust and perceived reliability had the largest standardised coefficient. The common-method diagnostic did not identify a dominant single factor, and regression diagnostic and robustness checks did not materially alter the substantive conclusions.

Discussion

The findings show that AI tools are embedded in the learning practices of many respondents, including finance-related learning. However, the results do not support a simple interpretation in which AI use itself produces better financial behaviour. Instead, different dimensions of AI engagement show different statistical relationships with students' self-reported financial behavioral outcomes. The measurement analysis further shows that perceptions of AI reliability and the behaviour of independently verifying AI-generated information should be treated separately.

AI Use and Financial Learning Among Students

Within this sample, high levels of awareness and use indicate that AI tools are integrated into students' learning routines for explanations, assignment support, material simplification, and self-paced learning. Digital resources also provide broader access to financial education and flexible learning formats (OECD, 2021). These findings are consistent with broader trends in higher education, where AI applications are increasingly linked to student support, adaptive learning, assessment, and intelligent tutoring systems (Zawacki-Richter et al., 2019). Nevertheless, these results should be interpreted as characteristics of the surveyed convenience sample and are not representative of the entire population. In the context of financial literacy, AI primarily functions as an explanatory support tool. Students utilize AI to learn about financial concepts, budgeting, saving, investment fundamentals, and related topics. This is advantageous, as financial literacy emphasizes practical application rather than solely theoretical knowledge. Digital resources enhance the accessibility and flexibility of financial education, particularly for learners who require repetition or tailored examples (OECD, 2021). However, the findings also indicate that AI should not be regarded as a professional financial advisor. AI is more appropriately considered a learning assistant that simplifies financial topics, while final judgement should remain with the learner, instructor, or a verified source.

Perceived Value, Trust, Reliability and Verification

A key finding is that AI trust and perceived reliability, as well as verification behavior, are both conceptually and empirically distinct constructs. Students generally perceived the value of AI for learning positively ($M = 3.77$), whereas the mean for AI trust and perceived reliability was more moderate ($M = 3.09$). Verification behavior exhibited a higher mean ($M = 3.86$), suggesting that many respondents reported verifying AI-generated information even when their overall trust in AI reliability was not particularly strong. This pattern supports the notion of calibrated, rather than unquestioning, reliance on AI. Financial literacy encompasses not only the receipt of information but also the evaluation and application of knowledge in practical contexts (Huston, 2010). In the regression analysis, AI trust and perceived reliability demonstrated the largest standardized coefficient ($\beta = 0.359$), while verification behavior also showed an independent positive association with self-reported outcomes ($\beta = 0.184$). These coefficients should not be interpreted as evidence of causal effects. Instead, the data indicate that respondents who exhibited greater trust in AI-generated information, as well as those who engaged in more frequent verification, tended to report stronger financial behavioral outcomes. The independence of these two variables is consistent with prior research indicating that effective human–AI interaction depends on trust that is calibrated to a system's reliability and limitations (Glikson & Woolley, 2020; Lee & See, 2004).

Meaning of the Non-Significant Finance-Related AI Use Result

Finance-related AI use exhibited a positive bivariate association with self-reported financial behavioral outcomes ($r = 0.357$), but it did not make a statistically significant unique contribution after perceived AI value, AI trust and perceived reliability, verification behaviour, and AI usage frequency were considered simultaneously. The standardized coefficient in the regression model was $\beta = 0.114$ ($p = 0.085$), and the 95% confidence interval for the unstandardized coefficient included zero. This result should not be interpreted as evidence of no relationship, but rather as an absence of a statistically significant unique association after controlling for other AI-related variables. One possible explanation is the substantial overlap between finance-related AI use and overall AI usage frequency ($r = 0.605$). Students who use AI more frequently are also more likely to use it for finance, suggesting that some of the bivariate relationship may reflect shared variance with general AI engagement. Another consideration is measurement: the finance-related AI-use index records whether students use AI for financial learning, budgeting, saving, and investment queries, but does not capture the depth, accuracy, or quality of those interactions. Exposure to financial information via AI is conceptually distinct from understanding, independently verifying, and appropriately applying that information. The independent associations observed for trust/reliability and verification behaviors support a more nuanced distinction between domain-specific exposure and responsible engagement. This interpretation aligns with financial education research, which demonstrates that exposure to information or instruction does not automatically result in lasting behavioral change (Fernandes et al., 2014).

Need for Guided and Critical AI Use

Concerns regarding privacy, over-dependence, inaccurate information, lack of human interaction, and insufficient personalization suggest that AI-supported financial education necessitates careful oversight. These challenges are particularly significant in financial contexts, where students may inadvertently disclose personal information or rely on AI-generated responses that are incomplete or inappropriate for their specific situations. The Consumer Financial Protection Bureau (2023) has similarly identified risks associated with chatbots in consumer finance, such as the dissemination of inaccurate information and limited capacity to provide human support when required. These findings underscore the importance of guided and critical use of AI in financial literacy education. The High-Level Expert Group on Artificial Intelligence (2019) emphasizes privacy, transparency, human oversight, and accountability as foundational elements of trustworthy AI. In the context of this study, these principles indicate that students should receive training not only in the use of AI tools but also in evaluating their reliability, comparing outputs with credible sources, safeguarding sensitive data, and discerning when to seek qualified human or professional advice. Collectively, the results support a responsible-engagement approach rather than a simple adoption model. Perceived AI value, trust, perceived reliability, verification behavior, and usage frequency were positively associated with self-reported financial behavioral outcomes, whereas the breadth of finance-related AI use did not demonstrate a statistically significant unique association after adjustment. Although the cross-sectional design precludes causal inference, it reveals patterns of association that warrant further longitudinal and experimental investigation.

Implications

The theoretical contribution of this study lies not in a full test of the Technology Acceptance Model but in an integrative, TAM-informed perspective on AI-supported financial learning. Perceived AI value draws on the technology-acceptance logic of usefulness and ease of use, while the framework adds responsible-engagement dimensions by distinguishing AI trust and perceived reliability from verification behaviour. This distinction is important, as the two dimensions are conceptually different and both were independently positively related to self-reported financial behavioral outcomes. In practical terms, the findings imply that institutions should focus less on promoting AI adoption alone and more on developing students' capacity to evaluate AI-generated financial information, verify important claims against textbooks, official sources, or teacher feedback, protect personal information, and recognise when professional guidance is appropriate. At the policy level, these results support the integration of AI literacy, digital verification skills, privacy awareness, and ethical AI use into financial-literacy education, consistent with international guidance emphasising human oversight, transparency, accountability, privacy, and human-centred AI (High-Level Expert Group on Artificial Intelligence, 2019; OECD, 2019; UNESCO, 2023). Because the evidence is cross-sectional and self-reported, these implications are framed as educational recommendations informed by observed associations rather than as demonstrated causal effects.

Limitations and Future Research

Limitations

The study has several limitations that should be considered when interpreting the findings. First, the outcome is based entirely on self-reported perceptions, including perceived improvement in financial awareness, perceived influence on decisions, saving and budgeting habits, and informed financial choices. The study therefore does not measure objectively tested financial literacy or directly observed financial behaviour. Second, the sample is limited to higher-education students and was obtained through convenience sampling. The sample should not be treated as representative of the broader student population. A large proportion of respondents belonged to commerce and management disciplines, which may have increased familiarity with financial concepts and further limits generalisability. The sensitivity analysis controlling for age, gender, and education did not materially change the main findings, but such statistical adjustment cannot overcome the limitations of non-probability sampling or disciplinary concentration. Third, verification behaviour was measured with a single item after being separated from the trust/reliability composite; future studies should use a validated multi-item verification scale.

Another limitation is the cross-sectional design. Because the predictor and outcome variables were collected at one point in time, the findings establish statistical associations rather than temporal ordering or causality. In addition, the predictors and outcome were collected from the same respondents through the same questionnaire. Harman's single-factor diagnostic indicated that the first unrotated factor accounted for 45.28% of the variance and did not dominate the covariance structure, but this screening test cannot rule out common-method variance. Future studies can reduce this concern by separating measurements in time, using multiple data sources, or incorporating objective indicators (Podsakoff et al., 2003). AI tools were evaluated in general terms rather than by specific platform. Individual tools may vary in accuracy, accessibility, and functionality.

Directions for Future Research

Future research should address these limitations by employing larger and more diverse probability-based or carefully stratified samples across regions, institutions, disciplines, and educational levels. Longitudinal designs are recommended to investigate temporal ordering and to determine whether AI-supported financial learning is associated with subsequent behavioral outcomes. Studies should integrate objective financial-literacy assessments or observed behavioral indicators with self-reported measures, and develop multi-item instruments that distinguish trust, perceived reliability, verification, and other forms of critical AI engagement. Comparative research on specific AI platforms may reveal whether differences in accuracy, design, or transparency correspond to distinct learning outcomes. Experimental and quasi-experimental studies could evaluate guided AI-supported financial-literacy modules, comparing unstructured AI use to instruction that explicitly requires source verification, explanation of uncertainty, and human oversight. These approaches would provide stronger evidence regarding the effectiveness of verification-oriented AI literacy interventions in improving financial knowledge or behavior. Additionally, future research could examine whether the relationship between finance-related AI use and financial outcomes is influenced by the quality, depth, or purpose of AI engagement, rather than solely by the frequency of finance-related AI use.

Conclusion

The present study examined AI use among higher-education students and analysed the associations of perceived AI value, AI trust and perceived reliability, verification behaviour, AI usage frequency, and finance-related AI use with self-reported financial behavioral outcomes. The measurement analysis distinguished trust/reliability perceptions from verification behaviour because item-level and conceptual evidence indicated that verification should not be treated as part of the same composite construct.

The surveyed sample showed high levels of AI awareness and use, and many respondents also reported using AI for finance-related learning. In the regression analysis, perceived AI value, AI trust and perceived reliability, verification behaviour, and AI usage frequency were significantly and positively associated with self-reported financial behavioral outcomes. The model accounted for 54.8% of the variance in the outcome, with trust in AI and perceived reliability exhibiting the largest standardized coefficients. AI use for financial purposes alone did not demonstrate a unique, statistically significant association with the outcome after controlling for other dimensions of AI engagement. The positive bivariate association between finance-related AI use and the outcome overlapped substantially with overall AI use frequency, and the finance-use index reflected breadth rather than depth or quality of engagement. These findings indicate a distinction between exposure to AI for financial topics and the quality of student engagement with AI-generated information. The results underscore the educational significance of fostering critical and responsible AI engagement, although causality cannot be inferred. Due to the cross-sectional design, convenience sampling, and reliance on self-reported perceptions, these findings should be interpreted as associations within the surveyed sample. A key challenge for educators and institutions is to enhance students' capacity to evaluate, verify, contextualize, and responsibly utilize AI-generated financial information, while maintaining teachers, credible sources, and qualified professionals as essential reference points.

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