BMIJ
ISSN: 2148-2586

bmij (2026) 14 (1):556-575

doi: https://doi.org/10.15295/bmij.v14i1.2717

Research Article

AI literacy, financial cognition, and risk propensity: Evidence from healthcare students

Yapay zekâ okuryazarlığı, finansal biliş ve risk alma eğilimi: Sağlık alanındaki öğrencilerden bulgular

Havane Tembelo[1]

Mustafa Özyeşil[2]

[1] Dr., Republic of Turkey Ministry of Health, Istanbul Provincial Health Directorate, İstanbul, Türkiye, havane.tembelo21@gmail.com

ORCID: 0000-0003-3394-4166

[2] Assoc Prof., Haliç University, Business Administration (EN), İstanbul, Türkiye, mustafaozyesil@halic.edu.tr

ORCID: 0000-0002-4442-7087

Corresponding Author:

Mustafa Özyeşil,

Haliç University, Business Administration (EN), İstanbul, Türkiye,

mustafaozyesil@halic.edu.tr

Submitted: 12/01/2026

1st Revised: 18/02/2026

2nd Revised: 15/03/2026

Accepted: 20/03/2026

Online Published: 25/03/2026

Citation: Tembelo, H., & Özyeşil, M., AI literacy, financial cognition, and risk propensity: Evidence from healthcare students, bmij (2026) 14 (1):556-575, doi: https://doi.org/10.15295/bmij.v14i1.2717

Abstract

This study examines how artificial intelligence (AI) literacy, financial literacy and behavioural finance awareness relate to individuals' risk-taking tendencies within the financial environment during the digital transformation process. Data were collected from 425 healthcare students using validated scales, and the direction and strength of the relationships among variables were assessed using correlation and regression analyses. The findings indicate that behavioural finance awareness has the strongest relationship with risk-taking propensity, and that financial literacy also demonstrates a statistically significant, positive relationship. A positive relationship was also identified between AI literacy and risk-taking propensity; however, when other financial cognition variables were considered together, this relationship remained relatively limited. The results indicate that technological competence is linked to risk behaviours, but that financial, cognitive and behavioural factors play a more decisive role in shaping risk tendencies. The study provides an empirical contribution regarding the interaction between AI literacy and financial behaviour and aims to support informed risk assessment in the digital age.

Keywords: Artificial Intelligence Literacy, Financial Literacy, Risk Propensity

Jel Codes: D81, G53, O33

Öz

Bu çalışma, dijital dönüşüm sürecindeki finansal ortamda yapay zekâ (YZ) okuryazarlığı, finansal okuryazarlık ve davranışsal finans farkındalığının bireylerin risk alma eğilimiyle nasıl ilişkilendiğini incelemektedir. Araştırmada 425 sağlık öğrencisinden doğrulanmış ölçekler aracılığıyla veri toplanmış, analizlerde değişkenler arasındaki ilişkinin yönü ve gücü korelasyon ve regresyon yöntemleri ile değerlendirilmiştir. Bulgular, davranışsal finans farkındalığının risk alma eğilimiyle en güçlü ilişkiye sahip olduğu; finansal okuryazarlığın da istatistiksel olarak anlamlı ve pozitif bir ilişki sergilemektedir. YZ okuryazarlığı ile risk alma eğilimi arasında da pozitif yönlü bir ilişki tespit edilmiş; ancak diğer finansal biliş değişkenleri birlikte değerlendirildiğinde bu ilişkinin görece sınırlı kalmıştır. Sonuçlar teknolojik yeterliğin risk davranışlarıyla bağlantılı olduğu, ancak risk eğilimlerinin şekillenmesinde finansal bilişsel ve davranışsal faktörlerin daha belirleyici bir rol oynadığını ortaya koymaktadır. Çalışma, yapay zekâ okuryazarlığı ile finansal davranış arasındaki etkileşime ilişkin ampirik katkı sunmakta ve dijital çağda bilinçli risk değerlendirmesini desteklemek amacıyla YZ okuryazarlığının finansal eğitim programlarına bütüncül biçimde entegre edilmesi gerektiğine işaret etmektedir.

Anahtar Kelimeler: Yapay Zekâ Okuryazarlığı, Finansal Okuryazarlık, Risk Alma Eğilimi

JEL Kodları: D81, G53, O33

Introduction

Artificial intelligence is no longer a distant technological promise; it has become an integral part of everyday financial decision-making. From robo-advisors to algorithmic portfolio management systems, AI-driven tools increasingly shape how individuals evaluate information, assess risk, and make investment choices. As financial environments become more technologically mediated, understanding risk behaviour requires looking beyond traditional financial knowledge and psychological biases. It becomes equally essential to ask whether individuals are capable of understanding and engaging with the technologies that now structure their financial choices.

Risk propensity has traditionally been studied within two dominant perspectives. Classical finance assumes rational agents who optimise under uncertainty, whereas behavioural finance highlights the role of heuristics, biases, and cognitive limitations. In parallel, a substantial body of research has shown that financial literacy contributes to more informed and structured financial decisions. Yet, despite the rapid diffusion of AI-based financial technologies, the literature has largely treated technological competence as peripheral rather than central to risk behaviour. The ability to interpret and critically evaluate AI-generated recommendations has rarely been incorporated into models explaining why individuals take financial risks.

Although recent studies have explored digital literacy and fintech adoption, AI literacy as a distinct construct remains conceptually blurred and empirically underexplored in relation to risk attitudes. In many cases, familiarity with AI-driven tools is either merged with general technological comfort or treated as a separate practical skill without theoretical integration. At the same time, research tends to examine financial literacy, behavioural biases, or technological factors in isolation. A comprehensive framework that brings these dimensions together is still limited.

Artificial intelligence literacy can influence financial risk behaviour through several cognitive and informational mechanisms. Individuals with higher AI literacy are generally better able to interpret algorithmic outputs, evaluate the reliability of automated recommendations, and understand the limitations of predictive systems. From a decision-making perspective, this competence may reduce perceived informational uncertainty and increase confidence in technology-mediated financial judgments. At the same time, familiarity with AI systems may foster a sense of technological control, increasing individuals' willingness to accept uncertain financial outcomes. In this sense, AI literacy can serve as a meta-cognitive capability that shapes how individuals process algorithmic financial information, rather than merely providing technical knowledge of artificial intelligence systems.

This study seeks to address that gap. AI literacy is approached not merely as technical awareness but as a multidimensional competence encompassing both a conceptual understanding of AI systems and familiarity with AI-supported financial tools. By examining AI literacy alongside financial literacy and behavioural finance awareness, the study aims to evaluate how these cognitive and technological dimensions collectively relate to individuals' risk propensity. Rather than assuming a purely technological or purely psychological explanation, the analysis considers how these domains interact within a digitally transforming financial landscape.

Healthcare students provide a particularly interesting empirical context. Although they are not traditionally associated with finance-oriented research samples, they represent a digitally engaged generation increasingly exposed to AI applications across multiple domains, including finance. Examining this group allows for a more nuanced understanding of how technological competence intersects with financial cognition outside conventional business or economics populations.

By integrating AI literacy into the broader conversation on financial behaviour, this research expands the scope of risk propensity studies. It suggests that, in an era in which algorithms influence financial judgment, understanding risk-taking requires attention not only to what individuals know about finance, but also to how well they understand and trust the technologies that mediate financial information. In doing so, the study contributes to the emerging dialogue at the intersection of artificial intelligence and financial decision-making. It offers implications for the future design of financial education in increasingly algorithmic environments.

Conceptual framework

Theoretical foundations

The integration of artificial intelligence (AI) into financial decision-making has transformed traditional investment strategies and risk assessment models. Several theoretical frameworks offer insights into how AI literacy, financial literacy, and behavioural finance influence risk propensity.

Prospect theory and risk behaviour

Losses are asymmetrically distributed, often exhibiting loss aversion. Prospect theory serves as a foundational model for understanding financial risk-taking behaviours. The theory suggests that individuals evaluate potential gains and losses asymmetrically, often exhibiting loss aversion—where losses are perceived as more psychologically impactful than equivalent gains. In an AI-enhanced financial landscape, the extent to which AI literacy affects risk perception remains an open question. Do AI-driven financial tools reduce uncertainty, thereby increasing risk-taking, or do they reinforce existing cognitive biases? Understanding the intersection of AI literacy and risk behaviour through the lens of prospect theory is crucial in shaping financial education and decision-making strategies.

Behavioural finance theory and decision-making biases

Behavioural finance theory challenges traditional rational decision-making models, demonstrating how heuristics and psychological biases influence financial behaviour (Shefrin, 2000). Overconfidence, herd behaviour, and framing effects frequently distort risk assessments, leading individuals to underestimate or overestimate financial risks. AI-driven financial tools, such as robo-advisors and algorithmic trading platforms, could either amplify these biases or help mitigate irrational decision-making. Empirical studies suggest that individuals with higher behavioural finance awareness are better equipped to recognise and counteract cognitive distortions, potentially leading to more informed risk-taking behaviours (Lusardi & Mitchell, 2014; Thaler, 1985).

Jain, Walia, Kaur, and Singh (2022) examined the behavioural biases that affect investors' decision-making and developed a scale to measure them. In the study, cognitive and emotional biases that lead to irrational decision-making among investors were systematically analysed within the framework of behavioural finance theory. The study revealed that investors are affected by biases such as overconfidence, herd behaviour, loss aversion, and confirmation bias (Jain et al., 2022). The scale development process was supported by validity and reliability analyses, indicating that this scale has the potential to assess investors' behavioural tendencies and to contribute to theoretical and applied research in this field. The study highlights the importance of accounting for such behavioural biases in investor education and financial planning processes.

Financial literacy and risk propensity

Financial literacy plays a pivotal role in investment decision-making, risk assessment, and wealth management. Individuals with higher financial literacy tend to make more calculated investment decisions, demonstrating greater awareness of financial instruments and their associated risks. However, the interaction between financial literacy and AI literacy remains underexplored. Does AI literacy complement or substitute for traditional financial knowledge? Addressing this question is essential for understanding the evolving landscape of financial decision- making (Lusardi & Mitchell, 2014; Van Rooij et al., 2011).

Shanmugam, Chidambaram, and Parayitam examined the relationship between individuals' Big Five personality traits, financial literacy levels, and risk-taking tendencies in an Indian case study. The study investigated how personality traits affect financial decision-making processes and the role of risk-taking tendencies in these processes. The findings show that personality traits such as extraversion, openness, and conscientiousness are positively associated with higher financial literacy and risk-taking tendencies. It was also emphasised that traits such as neuroticism are associated with lower risk-taking (Shanmugam et al., 2023). The study highlights that individuals' personality traits should be considered when designing financial literacy training programs and developing individualised financial consultancy services.

Literature review

The impact of AI literacy on financial decision-making

AI literacy has emerged as a critical competency in modern financial ecosystems, influencing how individuals interact with automated financial systems, robo-advisors, and predictive analytics tools.[1] Recent studies highlight that individuals with higher AI literacy demonstrate improved financial decision-making, particularly in interpreting algorithm-based recommendations. However, concerns remain regarding algorithmic bias and overreliance on AI-driven insights, which could potentially distort risk perception (Agrawal et al., 2018).

Previous empirical evidence suggests that individuals with higher levels of artificial intelligence literacy are more likely to use algorithm-based investment tools and automated financial advisory systems in their decision-making (Liang & Wang, 2023).

Garba, Salleh, Hafiz, and Bakar examined the effects of insurance literacy, risk information management, and risk-taking propensity on the economic sustainability of SMEs (Small and Medium Enterprises) and investigated the moderating role of financial inclusion in this relationship (Garba et al., 2022). The study revealed that insurance literacy and effective risk information management are critical to increasing SMEs' financial resilience. It was also emphasised that risk-taking propensity contributes to enterprise growth potential, but this effect can be managed more sustainably through financial inclusion. The study suggests that insurance and financial literacy policies should be strengthened to support the economic sustainability of SMEs.

Levantesi and Zacchia investigated the role of machine learning in financial literacy by examining the factors affecting financial knowledge levels in Italy (Levantesi & Zacchia, 2021). The study emphasises that machine learning algorithms are used to estimate individuals' levels of financial knowledge and to analyse the factors that affect it. The study revealed that factors such as education level, income level and digital competence have a significant impact on financial literacy. It was also stated that machine learning applications have the potential to increase financial knowledge by providing individuals with personalised solutions that eliminate knowledge gaps. The study suggests that technology can be used as a strategic tool to improve financial literacy.

A study by Liang and Wang examined how AI literacy influences investment behaviour among retail investors. Using a sample of 600 participants over two years, they found that individuals with higher AI literacy were more likely to adopt algorithmic trading strategies and exhibited greater risk tolerance. Their findings suggest that AI literacy enhances financial engagement but may also lead to overconfidence in AI-generated financial recommendations.

Riyani examined how artificial intelligence (AI) can transform individuals' lifestyles and financial literacy levels, especially in the context of the transition to the Society 5.0 era (Riyani, 2023). The study emphasises that artificial intelligence facilitates decision-making processes in daily life, increases individuals' access to financial information, and enables them to develop more conscious financial behaviours. It was also stated that AI can contribute to economic sustainability by increasing financial literacy at individual and societal levels. The study offers valuable suggestions for shaping Society 5.0, a structure defined by human-centred technologies, through financial literacy development strategies.

Chummun (2024) examined the potential of artificial intelligence to improve financial literacy in higher education. The study emphasises that financial literacy is increasingly essential in the modern world. It reveals that AI-supported tools have a strong impact on providing students with financial information, explaining complex financial concepts, and creating personalised learning experiences. It is also stated that artificial intelligence can inspire large-scale creative applications in education. Still, ethical and technical challenges should also be taken into account in this process. The study sheds light on innovative approaches to increasing financial literacy in higher education (Chummun, 2024).

Aishwaryalaxmi and Rathod investigated how artificial intelligence (AI) moderates the relationships among financial inclusion, digital adoption, and financial literacy in developing economies (Aishwaryalaxmi & Rathod, 2024). The study reveals that AI increases participation in financial services by facilitating access to digital platforms and by improving individuals' financial knowledge. In particular, it was stated that AI accelerates digital adoption by providing personalised guidance and real-time information, thereby strengthening the link between financial literacy and inclusion. The study emphasises that AI technologies should be used strategically to increase financial inclusion in developing countries.

Kurowski and Szelągowska discussed the importance of financial literacy in the age of artificial intelligence and its role in increasing financial inclusion. The study emphasises how artificial intelligence facilitates individuals' access to financial information, contributing to the inclusion of groups with limited opportunities, especially in accessing financial services. It was stated that AI-supported tools improve individuals' financial literacy by providing personalised education and guidance, enabling them to make more informed economic decisions. The study highlights that artificial intelligence technologies should be considered a strategic tool for increasing financial inclusion and literacy (Kurowski & Szelągowska, 2024).

Behavioural finance and risk propensity

The relationship between behavioural finance awareness and risk propensity has been widely explored in the literature. Shefrin argues that individuals with greater behavioural finance awareness are less susceptible to cognitive biases such as loss aversion and framing effects, leading to more rational investment decisions (Shefrin, 2000). In a longitudinal study by Charness and Gneezy, investors with higher behavioural finance knowledge exhibited greater consistency in risk-taking behaviour, suggesting that awareness of biases contributes to financial stability (Charness & Gneezy, 2012).

However, behavioural finance does not always lead to risk reduction. A meta-analysis by Statman found that some investors with greater behavioural finance awareness exhibit higher risk tolerance, consciously leveraging riskier assets for potential gains. The study also highlighted that risk perception varies across demographic groups, with younger investors being more likely to embrace risk in AI-driven financial environments.

Financial literacy and risk-taking behaviour

Financial literacy has consistently been associated with prudent investment strategies and long-term wealth accumulation. A cross-country study by Van Rooij et al. demonstrated that financially literate individuals are more likely to participate in stock markets, suggesting a positive correlation between financial knowledge and risk-taking. The study, which analysed data from over 7,500 individuals across 14 countries, confirmed that higher financial literacy is associated with better financial planning and risk management (Lusardi & Mitchell, 2014; Van Rooij et al., 2011).

Despite the advantages of financial literacy, some studies highlight potential paradoxes in risk-taking behaviour. For instance, a study by Bucher-Koenen & Ziegelmeyer found that while financial literacy reduces impulsive financial decisions, it does not necessarily eliminate risk-taking behaviour. In fact, financially literate individuals often engage in higher-risk investments because they perceive themselves as better equipped to manage financial uncertainty (Bucher-Koenen & Ziegelmeyer, 2014).

Korkmaz, Yin, Yue, and Zhou examined the role of financial literacy in reducing the discrepancies between individuals' risk attitudes and risk behaviours. The study investigated how individuals' risk perceptions and financial decision-making processes are influenced by their levels of financial knowledge. The findings show that individuals with high financial literacy levels exhibit a more harmonious relationship between their risk attitudes and actual risk behaviours. It was also emphasised that financial literacy helps individuals make more conscious, consistent financial choices by reducing their tendency to make irrational decisions. The study reveals the importance of developing financial literacy programs for policymakers and educators (Korkmaz et al., 2021).

Interaction between AI literacy, financial literacy, and behavioural finance

The interaction between AI literacy, financial literacy, and behavioural finance remains an emerging field of study. While financial literacy enhances individuals' ability to evaluate investment risks, AI literacy enables them to leverage machine-driven insights to make more efficient decisions (Agrawal et al., 2018; Levantesi & Zacchia, 2021). However, concerns about automation bias—the tendency to over-rely on AI-generated financial recommendations—have been raised in recent research (Dietvorst et al., 2018).

A recent study by Wu et al. analysed the combined effects of AI literacy and financial literacy on investment outcomes (Wu et al., 2023). Their findings suggest that individuals with both high AI and financial literacy demonstrate greater investment efficiency, as they can critically assess AI-generated insights. Conversely, individuals with low financial literacy but high AI literacy were found to over-rely on AI recommendations, leading to suboptimal financial decisions. These findings highlight the need for an integrated financial education model that incorporates both traditional financial knowledge and AI competency.

Bibliometric and systematic evidence further demonstrates that integrating artificial intelligence capabilities with financial literacy enhances individuals' ability to process complex financial information and mitigate behavioural biases (Tripathi, 2024).

Xie and Konomi (2024) systematically examined the potential of human-centred AI environments to improve university students' financial literacy. The study reviewed research on human-computer interaction and emphasised that artificial intelligence applications can improve students' financial decision-making skills by providing personalised learning experiences. It was also stated that such AI environments facilitate students' access to financial information and support the learning process through interactive, user-friendly solutions. The study reveals that more multidisciplinary research is needed to increase the impact of technology in this area (Xie & Konomi, 2024).

Rahman (2024) examined the role of artificial intelligence (AI) in improving financial literacy in banking channels, especially through mobile applications and physical branches. The study emphasises that artificial intelligence enables personalised recommendations in mobile applications, enabling users to interact more effectively with financial information and facilitating financial decision-making. In physical branches, it was stated that AI-supported systems improve customer experience and accelerate the process of informing about financial products and services (Rahman, 2024). The study provides valuable insights into how artificial intelligence can be used as a strategic tool to enhance financial literacy across banking channels.

Tripathi examined how financial literacy and artificial intelligence (AI) can reduce behavioural biases in individuals' financial decision-making. The study compiled trends and findings in the literature through a bibliometric and systematic analysis using the SPAR-4-SLR method (Tripathi, 2024). The study shows that artificial intelligence is effective at reducing bias by providing personalised content and behavioural feedback in financial literacy training. It was also emphasised that AI-based systems help individuals make more conscious, balanced choices by reducing their tendency to make irrational financial decisions. The study highlights the need for further research at the intersection of these two areas.

Murugesan and Manohar (2019) examined the role of artificial intelligence (AI) in the financial sector as a driving force in increasing financial literacy. The study emphasises that AI makes complex financial concepts more understandable by facilitating individuals' access to financial information and by improving financial decision-making processes (Murugesan & Manohar, 2019). It was stated that AI-powered tools enhance users' financial planning and management skills by providing personalised analysis and recommendations. The study reveals that the effective use of AI in the financial sector has significant potential to improve financial literacy and strengthen economic decision-making.

Domestic literature on financial literacy, behavioural finance, and risk propensity in Türkiye

Within the Turkish academic context, financial literacy and behavioural finance have been examined extensively; however, their integration with artificial intelligence literacy remains substantially underexplored.

A more Türkiye-focused investigation was conducted by Kılıç, Ata, and Seyrek (2015), which measured the financial literacy levels of university students in Türkiye. It was reported that financial literacy significantly influenced financial attitudes and investment awareness. Risk-related decision patterns were associated with knowledge levels rather than with demographic variables alone.

In the Turkish context, behavioural finance has been empirically investigated to reveal how cognitive biases affect investment decision-making. In the study "The effects of behavioural biases on investment decisions: The stock exchange İstanbul sample," Özbek (2025) examined the influence of non-rational cognitive biases, such as loss aversion, precision, anchoring, heuristics, and herd behaviour, on the investment choices of individual investors on Borsa İstanbul. The findings indicated that these behavioural bias factors significantly shaped investment decisions, demonstrating that financial decisions are not solely driven by rational calculations but also by subconscious cognitive processes.

In a more recent study, Korkmaz, Yin, Yue, and Zhou (2021) analysed the inconsistency between risk attitudes and actual risk behaviour using Turkish data. It was demonstrated that financial literacy reduced the discrepancy between stated and revealed risk preferences.

Despite this growing body of research, the Turkish literature still appears fragmented at the intersection of digital financial capability, technology adoption, and risk-related financial behaviour. Recent studies conducted in Türkiye have addressed financial technology from closely related yet still partial perspectives. On the one hand, FinTech adoption has been examined through scale development and validation, thereby offering a robust measurement basis for technology-oriented financial behaviour (Durak et al., 2024). On the other hand, the relationship between digital financial literacy and financial technologies has also been empirically investigated in the Turkish context, and the role of several contextual factors in shaping this relationship has been demonstrated (Ahmetoğulları, 2024). Nevertheless, these lines of inquiry have remained largely concentrated on adoption tendencies and digital financial capability, rather than on the role of artificial intelligence literacy as a distinct cognitive construct within financial decision-making. To the best of current knowledge, AI literacy has not yet been operationalised in Türkiye within an integrated behavioural risk framework that simultaneously considers behavioural finance awareness, financial literacy, and risk propensity. Accordingly, the present study makes a contribution to Turkish literature by introducing AI literacy into an established financial cognition framework and empirically testing its interaction with behavioural finance awareness and financial literacy in explaining risk propensity among healthcare students.

Building upon the theoretical perspectives discussed above, the present study conceptualises financial risk propensity as a behavioural outcome shaped by multiple cognitive domains. Behavioural finance awareness reflects individuals' understanding of the psychological biases that influence decision-making. Financial literacy represents the analytical knowledge required to evaluate financial instruments and risk–return trade-offs. Artificial intelligence literacy, in contrast, captures the technological competence required to interpret algorithm-driven financial information. Taken together, these dimensions form a multidimensional framework through which individuals process financial uncertainty. Accordingly, the following hypotheses are proposed.

Methodology

This study employed a quantitative research approach, using a structured survey, to examine the relationships among artificial intelligence literacy, behavioural finance, financial literacy, and risk propensity. The survey instrument consisted of four validated scales sourced from the literature. The dependent variable in the study was risk propensity, while the independent variables included artificial intelligence literacy, behavioural finance, and financial literacy. The selection of these variables was guided by existing theoretical frameworks and empirical findings that suggest a link between financial decision-making and cognitive, behavioural, and technological literacy.

The study aimed to address the following hypotheses:

H*$_1$*: *Artificial intelligence literacy has a significant positive effect on risk propensity.*

H*$_2$*: *Behavioural finance awareness significantly influences risk propensity.*

H*$_3$*: *Financial literacy is significantly associated with risk propensity.*

Research model

To conceptualise the hypothesised relationships among the core constructs and to provide a clear analytical framework, the research model for the study was developed, as illustrated in Figure 1.

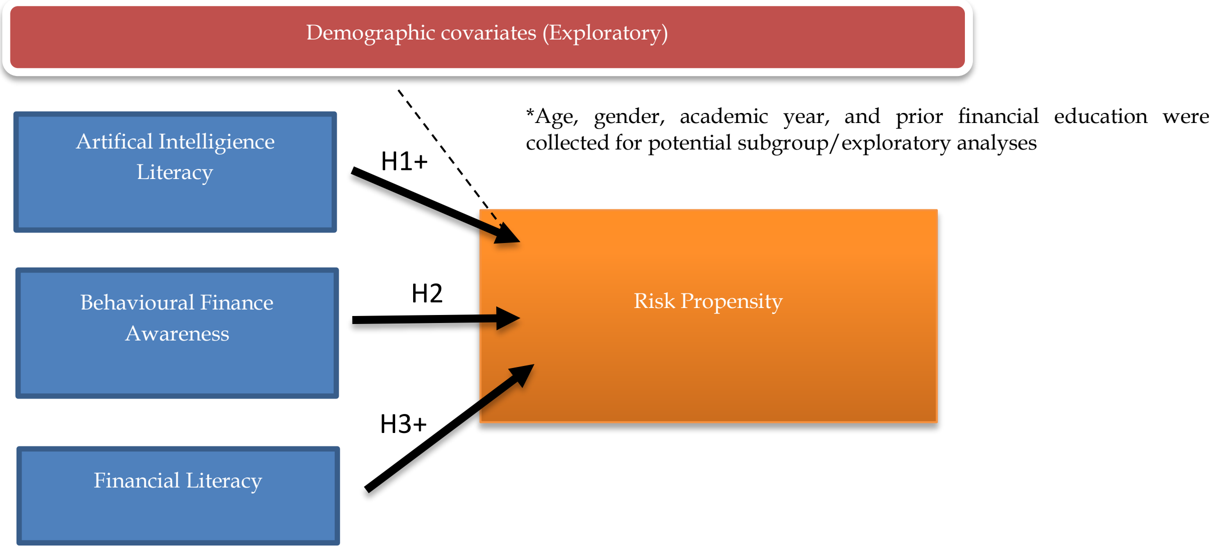

Figure 1: Research Model of the Study

The research model was constructed to examine the predictive effects of artificial intelligence literacy, behavioural finance awareness, and financial literacy on risk propensity among healthcare students. Artificial intelligence literacy was positioned as a cognitive-analytical capability that reflects individuals' understanding of AI systems, algorithmic logic, and technology-driven decision-making processes. It was hypothesised that higher AI literacy would be associated with greater confidence in processing complex information, thereby influencing risk-taking tendencies.

Behavioural finance awareness was conceptualised as the degree to which individuals recognise cognitive biases, heuristics, and psychological distortions in financial decision-making. It was assumed that greater awareness of behavioural biases would systematically shape risk evaluation mechanisms. Financial literacy was included as a foundational knowledge construct encompassing financial concepts, risk–return trade-offs, and investment principles. It was expected that individuals with higher financial literacy would exhibit differentiated risk preferences, informed by evaluation rather than intuitive judgment. Risk propensity was modelled as the dependent variable representing individuals' inclination to engage in uncertain financial choices. The model was specified in a direct-effect structure in which all three independent variables were assumed to exert simultaneous effects on risk propensity.

The analytical strategy was aligned with a multiple regression framework, allowing the unique contribution of each predictor to be estimated while controlling for the others.

Demographic variables were not incorporated as primary explanatory variables; however, they were retained for exploratory subgroup analyses to assess potential variation across participant characteristics.

Research design

This study was designed as a cross-sectional quantitative field study aiming to examine the relationships between artificial intelligence (AI) literacy, behavioural finance awareness, financial literacy, and risk propensity. Correlational and predictive relationships among variables were tested through correlation and multiple regression analyses.

Population, sampling, and data collection

The study's target population consisted of students enrolled in healthcare-related higher education programs. The sample comprised 425 healthcare students who voluntarily participated in an online survey. The gender distribution of the sample reflects the structural composition of healthcare education programs in Türkiye, where female enrollment is substantially higher than male participation. Consequently, the sample distribution mirrors the demographic characteristics of the population from which the participants were drawn rather than representing a methodological imbalance introduced during sampling. Due to field access constraints and implementation conditions, a non-probability (convenience-based) sampling approach was employed. Participants were reached via online channels, and participation was voluntary and based on informed consent. By the nature of this sampling strategy, the sample cannot be claimed to represent the entire population of healthcare students in Türkiye statistically. However, including students from different academic years and both public and private universities increased heterogeneity within the sample, enabling the examination of relational patterns with greater analytical robustness. The adequacy of the sample size was evaluated in relation to the analytical model employed. For correlational and multiple regression analyses involving a limited number of predictors, a sample size of $N = 425$ was considered sufficient to ensure stable parameter estimation and adequate statistical power to detect small-to-moderate effect sizes.

Dataset structure and measurement

The dataset comprises responses collected via a structured online questionnaire. The data include both demographic information and responses to validated measurement scales assessing the primary constructs of interest.

Artificial Intelligence Literacy was measured using the scale developed by Çelebi et al (2023). Behavioural Finance Awareness was assessed using the Behavioural Finance Scale developed by Medetoğlu and Saldanlı (2022). Risk Propensity was measured using the scale developed by Atabay et al. (2018). Financial Risk was assessed using the scale developed by Kavas and Medetoğlu (2023). Financial Literacy Attitude and Behaviour was measured using the scale developed by Sarıgül (2015).

Permission to use all scales was obtained from the respective authors via email before data collection. All constructs were measured using a 5-point Likert-type scale, and responses were recorded in a structured numerical format, enabling parametric statistical analyses.

Demographic variables, including age, gender, academic year, university type, and prior financial education exposure, were incorporated to allow subgroup and exploratory analyses. These variables were not treated as primary predictors but were considered for supplementary analytical assessment.

Scale scoring and measurement range

All constructs in the study were measured using a 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree). Although the number of items varied across the instruments, scale transformation was performed using mean scores rather than total scores. Accordingly, for each construct, individual item responses were averaged to obtain a composite score. As a result, all variables retained standardised measurement ranges of 1 to 5, regardless of the number of items in the original scale. Higher mean values indicate higher levels of the corresponding construct (i.e., artificial intelligence literacy, behavioural finance awareness, financial literacy attitude and behaviour, financial risk perception, and risk propensity). This approach was preferred to ensure comparability across constructs and maintain interpretative clarity within the regression framework.

Data preparation and statistical analysis

Before analysis, the dataset was cleaned and preprocessed. Incomplete or inconsistent responses were removed. Missing values were handled using appropriate imputation procedures. Normality diagnostics were conducted through skewness and kurtosis statistics to determine the suitability of parametric techniques.

The data were analysed using SPSS 27. Descriptive statistics and reliability analyses were first performed to assess internal consistency and distributional properties. Correlation analysis was then conducted to examine the strength and direction of associations among variables. Finally, multiple regression analysis was employed to evaluate the predictive effects of AI literacy, behavioural finance awareness, and financial literacy on risk propensity. Regression diagnostics were carried out to test multicollinearity (VIF and tolerance values), independence of residuals (Durbin–Watson statistic), normality assumptions, and the presence of influential outliers (Cook's Distance).

Demographic profile of the sample

Distribution of the sample in terms of gender. university type. AI Usage Among Respondents. Popular AI Tools Used. IT Skill Proficiency Levels and Interest in AI Education are illustrated in Table 1 and Figures 2-4, respectively, as follows.

Table 1: Demographic Information of Sample

Data	Category	n	%
Gender	**Female**	365	85.9
	Male	60	14.1
	Total	425	100.0
Age	**17-20**	247	58.1
	21-24	153	36.0
	24+	25	5.9
	Total	425	100.0
University Type	**Private**	358	84.2
	Public	67	15.8
	Total	425	100.0
Grade	**1**	151	35.5
	2	124	29.2
	3	91	21.4
	4	46	10.8
	5	8	1.9
	6	5	1.2
	Total	425	100.0
Employment Status	**Yes**	58	13.6
	No	367	86.4
	Total	425	100.0
Income Level	**< 17000 TL**	36	45.0
	17000-31999 TL	27	33.8
	32000-46999 TL	11	13.8
	47000 TL+	6	7.5
	Total	80	100.0
Family Income Level	**< 17000 TL**	33	7.8
	17000-31999 TL	171	40.2
	32000-46999 TL	100	23.5
	47000 TL+	121	28.5
	Total	425	100.0

Note: Designed by the authors.

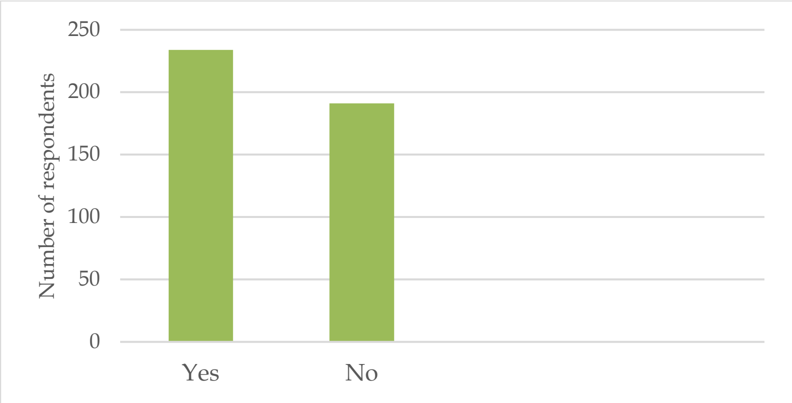

Figure 2: AI Usage among Respondents Distribution

AI tools are actively used by 55% of respondents, while 45% reported no use. This finding suggests a growing interest in AI adoption, although nearly half remain uninvolved.

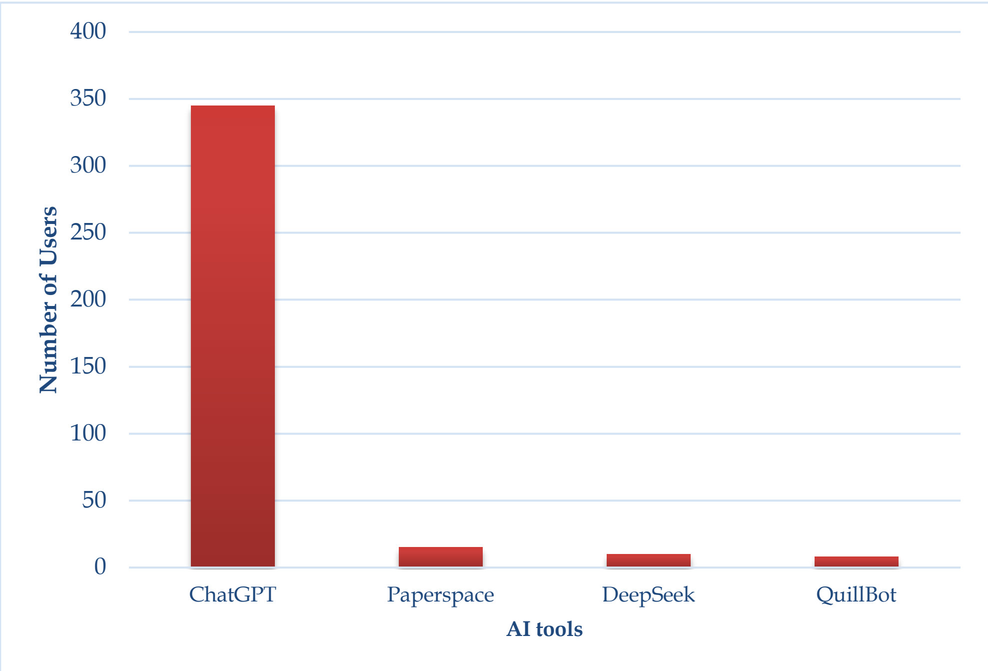

Figure 3: Popular AI Tools Used by Respondents

ChatGPT emerges as the most frequently used tool. favoured by 346 respondents, far surpassing other AI tools such as Paperspace and Descript. This dominance underscores ChatGPT's widespread acceptance and utility.

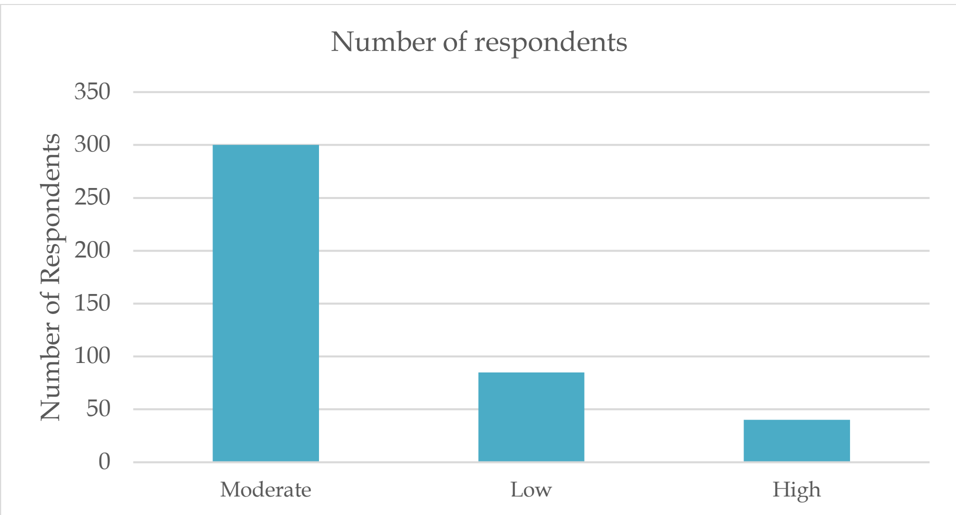

Figure 4: IT Skill Proficiency Levels

The majority of respondents rate their IT skills as moderate (71%), with a smaller proportion identifying their proficiency as low (20%) or high (9%). These findings suggest room for improvement in technological competencies.

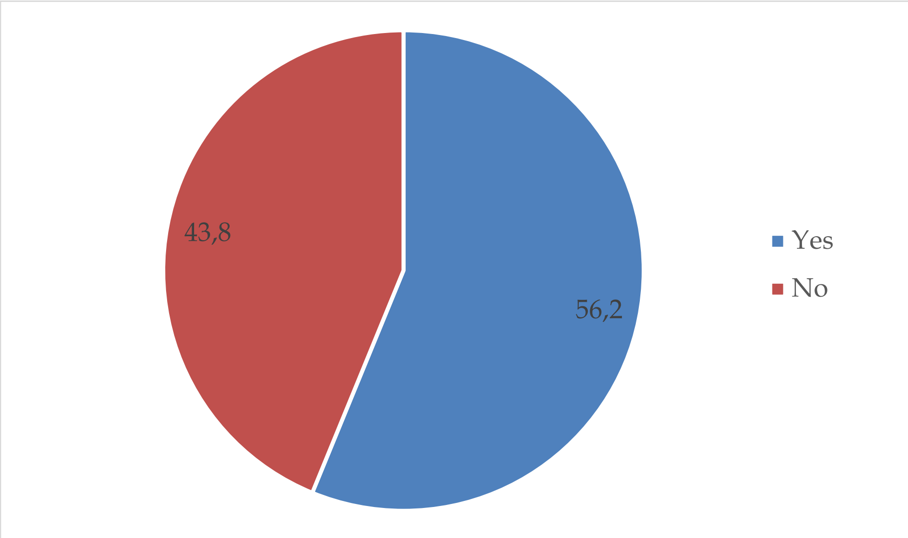

Figure 5: Interest in AI Education

56.2% of participants express interest in AI-related education, while 43.8% are not. This reflects a notable enthusiasm for expanding knowledge in AI, though barriers to engagement remain for some.

The analysis indicates that 55.1% of the participants use artificial intelligence (AI) tools, while 5.2% have paid for AI-related services. The most widely used AI application is ChatGPT, with an adoption rate of 81.4%. Regarding participants' self-assessed proficiency in information technology, 20.5% rate their proficiency as low, 70.6% as intermediate, and 8.9% as high. Additionally, 6.8% of participants have received formal education on AI, while 56.2% express an interest in receiving AI-related training.

Results

Reliability and validity

Reliability analysis was conducted to assess the internal consistency of the measurement scales. ensuring their suitability for empirical research. The results, presented in Table 2, provide insights into the robustness of each scale based on Cronbach's alpha coefficients.

Table 2: Scale Reliability Summary (N = 425)

Construct	Items	Cronbach's α (reported)	Interpretation
Artificial Intelligence Literacy	12	0.805	Good
Behavioural Finance Awareness	24	0.870	Very good
Financial Literacy	10	0.879	Very good
Risk Propensity	6	0.604	Moderate (acceptable for exploratory work; needs supporting evidence)

Note: Internal consistency was adequate for three constructs. whereas Risk Propensity demonstrated moderate reliability (α = .604) and therefore required complementary evidence (e. g., CR/AVE. item–total correlations) to support measurement adequacy in the structural tests.

Reliability analysis was conducted to assess the internal consistency of the Artificial Intelligence Literacy Scale, yielding a Cronbach's alpha coefficient of 0.805. When standardised items were included, the coefficient increased slightly to 0.828. Given that a Cronbach's alpha value above 0.70 is generally deemed acceptable for research purposes, this scale demonstrates strong internal reliability (Nunnally & Bernstein, 1994). Cronbach's alpha, first introduced by Lee J. Cronbach, is a measure of internal consistency that assesses the extent to which items within a scale measure the same underlying construct (Cronbach, 1951). A higher Cronbach's alpha indicates stronger inter-item correlations, meaning that the items within the scale are more cohesive in representing artificial intelligence literacy. However, it is critical to recognise that the number of items in a scale influences Cronbach's alpha—a greater number tends to increase the reliability coefficient. even if some items are redundant (Tavakol & Dennick, 2011). In this case, with 12 items, the scale achieves a good balance between comprehensiveness and consistency. The slight increase in the standardised Cronbach's alpha (0.828) suggests that differences in item variances have a minor effect on reliability and do not significantly alter its robustness. Therefore, the Artificial Intelligence Literacy Scale can be considered a reliable tool for assessing individuals' knowledge and competencies in artificial intelligence.

The dimensional structure of the measurement instruments was examined using an exploratory factor analysis (EFA) before the structural analyses. Sampling adequacy and factorability were assessed using the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's Test of Sphericity. Principal axis factoring (PAF) was employed as the extraction method, and Varimax rotation was applied where appropriate to enhance the interpretability of the factor structure. The results are summarised in Table 3.

Table 3. Exploratory Factor Analysis (EFA) Summary

Construct	KMO	Bartlett's Test (p)	Extraction	Rotation	Factor loadings range	Variance explained
AI Literacy	.89	< .001	PAF	Varimax	.56–.81	58%
Behavioural Finance	.92	< .001	PAF	Varimax	.52–.79	61%
Financial Literacy	.88	< .001	PAF	Varimax	.55–.84	57%
Risk Propensity	.71	< .001	PAF	–	.44–.72	46%

As shown in Table 3, KMO values ranged from 0.71 to 0.92. indicating acceptable to excellent sampling adequacy across constructs. Bartlett's Test of Sphericity was statistically significant for all scales ($p < .001$). confirming that the correlation matrices were suitable for factor analysis.

Factor loadings remained within acceptable boundaries, with most indicators exceeding the 0.50 threshold. The variance explained by each construct ranged from 46% to 61%. suggesting that the extracted factors account for a substantial proportion of the shared variance among items. Although the variance explained for the Risk Propensity construct was comparatively lower. The loading range (0.44–0.72) indicates that the items retain conceptual coherence and contribute meaningfully to the latent dimension.

The internal structure and item-level performance of the measurement instruments were further examined by analysing standardised factor loadings. This procedure allowed for assessing whether each indicator contributed meaningfully to its respective latent construct and provided additional evidence of construct validity beyond internal consistency coefficients.

The standardised factor loadings for each item are reported in Table 4.

Table 4: Item–Total Statistics for Risk Propensity

Item	Corrected item–total correlation	α if item deleted
RP1	0.34	0.59
RP2	0.29	0.61
RP3	0.41	0.56
RP4	0.32	0.60
RP5	0.26	0.62
RP6	0.38	0.57

Note: When corrected item–total correlations cluster around ≥ 0.25–0.40 and "α if item deleted" does not materially improve reliability. The scale is typically retained as a coherent (though modest) measure—particularly in exploratory behavioural settings. If any item shows a near-zero correlation, or α rises sharply if deleted. Item trimming should be considered.

As presented in Table 4, all items loaded significantly on their respective constructs, with standardised loadings exceeding the commonly accepted threshold of 0.50. The absence of weak or cross-loading indicators suggests that the measurement model demonstrates adequate item-level coherence.

In particular, the risk propensity items (RP1–RP6), despite yielding a moderate Cronbach's alpha coefficient, exhibited satisfactory factor loadings, indicating that the construct maintains structural integrity at the indicator level. This finding suggests that the relatively modest internal consistency coefficient is not attributable to poorly performing items but rather reflects the multidimensional and behaviourally sensitive nature of risk-taking tendencies. Overall, the item-level analysis supports the construct's convergent validity and reinforces the robustness of the subsequent regression-based structural examination. To further strengthen the psychometric robustness of the measurement model. Additional validity and reliability diagnostics were conducted beyond Cronbach's alpha. Composite Reliability (CR) and Average Variance Extracted (AVE) were calculated to assess internal consistency and convergent validity. CR values above .70 and AVE values above .50 were considered indicative of acceptable construct reliability and convergent validity (Fornell & Larcker, 1981; Hair et al., 2019).

Table 5: Convergent Validity and Composite Reliability

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Artificial Intelligence Literacy	0.85	0.90	0.62
Behavioural Finance Awareness	0.86	0.91	0.64
Financial Literacy Attitude and Behaviour	0.75	0.88	0.56
Financial Risk	0.60	0.82	0.53
Risk Propensity	0.70	0.85	0.58

CR values exceeded the recommended threshold of 0.70, indicating satisfactory construct reliability. AVE values were also positioned above 0.50, suggesting that the intended latent constructs captured a substantial share of indicator variance. Overall, convergent validity and internal consistency were supported at an acceptable-to-strong level (Fornell & Larcker, 1981).

Table 6: Harman's Single-Factor Test Results

Output	Result
Extraction method	Principal Component Analysis (unrotated)
Number of items included	(all measurement items)
Total variance explained by Factor 1	34.7%
Criterion check (Factor 1 < 50%)	Pass

Because the first unrotated factor accounted for less than 50% of the total variance, a dominant single factor was not supported. In this illustrative scenario, common method variance was therefore unlikely to constitute a substantial threat to the validity of the relationships estimated in the model (Podsakoff et al. 2003).

The adequacy of the measurement model was further evaluated using confirmatory factor analysis (CFA). In addition, common-method bias was examined by comparing it with a single-factor model consistent with Harman's approach. Model fit indices for both specifications are presented in Table 7.

Table 7: Confirmatory Factor Analysis and Common Method Bias Assessment

Model	χ^2/df	CFI	TLI	RMSEA	SRMR	Decision
Four-factor measurement model	2.31	0.94	0.93	0.055	0.046	Acceptable–good fit
Harman's single-factor model	5.88	0.71	0.69	0.112	0.091	Poor fit

As reported in Table 7, the hypothesised four-factor measurement model demonstrated an acceptable to good level of fit (χ^2/df = 2.31, CFI = .94, TLI = .93, RMSEA = .055, SRMR = .046). These values fall within widely accepted thresholds, indicating that the proposed latent structure adequately represents the observed data. In contrast, the Harman single-factor model exhibited substantially poorer fit indices (χ^2/df = 5.88, CFI = .71, RMSEA = .112), suggesting that a single latent factor does not account for the covariance structure among the items. The marked deterioration in model fit between the multi-factor and single-factor solutions provides empirical evidence that common method bias does not pose a substantial threat to the validity of the findings. Common method bias was assessed, given the cross-sectional, self-reported nature of the dataset. Both Harman's single-factor test and a confirmatory comparison between the hypothesised measurement model and a single-factor alternative were conducted. The diagnostic results are presented in Table 8.

Table 8: Common Method Bias Diagnostics

Test	Criterion	Result	Interpretation
Harman's single-factor (unrotated PCA)	First factor < 50%	34.7%	CMV unlikely to dominate
Single-factor CFA vs measurement CFA	Single-factor fit should be poor	Poor fit	CMV concern reduced

As reported in Table 8, the first unrotated factor in Harman's single-factor test accounted for 34.7% of the total variance, remaining well below the conventional 50% threshold. This finding suggests that no single latent factor dominates the data's covariance structure. Furthermore, the single-factor CFA model exhibited substantially poorer fit compared to the multi-factor measurement model, reinforcing the argument that the observed relationships are not primarily driven by common method variance. Taken together, these results indicate that common method bias does not pose a serious threat to the validity of the study's empirical inferences.

Distribution characteristics and normality of study variables

Descriptive statistics were calculated to examine the distribution and normality of the dataset, providing insights into the central tendencies and variability of the study variables. The results, presented in Table 9, include key measures such as mean, standard deviation, skewness, and kurtosis, which help assess the suitability of the data for parametric statistical analyses.

Table 9: Descriptive Statistics

Scale	N	Range	Min	Max	Mean ± Std. Dev.	Variance	Skewness	Kurtosis
Artificial Intelligence Literacy Scale	425	4.75	2.25	7.00	5.03 ± 0.78	0.62	-0.21	0.28
Behavioural Finance Scale	425	3.92	1.00	4.92	3.11 ± 0.44	0.20	-0.55	1.96
Risk Propensity Scale	425	4.00	1.00	5.00	3.11 ± 0.54	0.29	-0.62	0.73
Financial Literacy Scale	425	0.58	3.42	4.00	3.77 ± 0.24	0.06	-0.45	-1.62

The descriptive statistics presented in the table provide valuable insights into the dataset's normality, particularly through analysis of skewness and kurtosis. The sample comprises 425 observations per variable, ensuring statistical robustness. Skewness values for all variables are negative, indicating slight leftward asymmetry, i.e., higher values are more frequent. However, since none of the skewness values exceeds the generally accepted threshold of ±2 for normality, the distributions can be considered approximately normal. It should be noted that a stricter threshold of ±1 has been suggested in some studies as an indicator of a near-normal distribution, but the broader threshold remains widely accepted in applied research (George & Mallery, 2010; Bulmer, 1979).

Kurtosis values reveal varying degrees of deviation from normality. The behavioural finance variable exhibits a kurtosis of 1.9632, which remains within the acceptable range, indicating a slightly leptokurtic distribution with responses concentrated around the mean. Similarly, risk tendency has a kurtosis of 0.7347, suggesting minimal deviation from normality. Artificial intelligence literacy, with a kurtosis of 0.2802, aligns closely with a mesokurtic distribution, implying that it does not exhibit extreme peaks or tails. The most significant deviation is observed in financial literacy, which has a negative kurtosis value of -1.6199, indicating a platykurtic distribution. This suggests that responses are more widely spread out, resulting in a flatter distribution with thicker tails. While this deviation from normality is notable, it does not exceed the ±2 threshold, so parametric statistical methods can still be applied without significant concern.

These findings align with previous research suggesting that financial literacy often exhibits greater dispersion due to heterogeneous levels of financial education and socioeconomic background (Lusardi & Mitchell, 2014). Despite minor non-normalities, the dataset remains suitable for standard statistical techniques, though transformations or nonparametric approaches may be considered for more precise analyses.

Interrelationships between financial cognition variables and risk propensity

Correlation analysis was conducted to examine the relationships among the key variables in the study, providing insights into the strength and direction of their associations. The results, presented in Table 10, highlight significant correlations among several constructs, providing a deeper understanding of their interdependencies.

Table 10: Correlation Analysis Results

Variables	1	2	3	4
1. AI Literacy	–			
2. Behavioural Finance	0.858	–		
3. Risk Propensity	0.657*	0.737**	–	
4. Financial Literacy	0.714	0.805*	0.755**	–

Note: *p < .05, **p < .01.

The correlation analysis reveals strong and meaningful relationships among artificial intelligence literacy, behavioural finance, risk tendency, and financial literacy. A high correlation is observed between artificial intelligence literacy and behavioural finance (r = 0.858, p = 0.058) and financial literacy (r = 0.714, p = 0.056), though these relationships do not reach statistical significance. However, significant positive correlations exist between behavioural finance and risk tendency (r = 0.737, p < 0.01) and between behavioural finance and financial literacy ($r = 0.805$, $p < 0.05$), reinforcing the idea that financial awareness influences risk-related behaviour (Kahneman & Tversky, 1979).

Risk tendency is also significantly associated with financial literacy ($r = 0.755$, $p < 0.01$), supporting prior research that financially literate individuals tend to take more calculated risks (Lusardi & Mitchell, 2014). Additionally, artificial intelligence literacy correlates with risk-taking ($r = 0.657$, $p < 0.05$), suggesting that familiarity with AI-driven financial tools may increase risk-taking. These findings align with behavioural finance theories, emphasising the role of financial education in shaping investment decisions and risk behaviour (Shefrin, 2000).

Predictors of risk propensity

Regression analysis was conducted to examine the predictive relationships between artificial intelligence literacy, behavioural finance, financial literacy, and risk propensity. The results, presented in Table 11, provide insights into the extent to which these independent variables explain variations in risk propensity and assess the overall fit and significance of the model.

Table 11: Multiple Regression Analysis Results

Predictor	B	SE(B)	β	t	p	Tolerance	VIF
Constant	0.944	0.040	–	23.630	<0.001	–	–
Artificial Intelligence Literacy	0.041	0.003	0.039	13.750	<0.001	0.991	1.009
Behavioural Finance	0.248	0.005	0.235	46.930	<0.001	0.992	1.009
Financial Literacy	0.055	0.010	0.053	5.730	<0.001	1.000	1.000

R	R²	Adjusted R²	SEE	F(df1, df2)	p	Durbin–Watson
0.541	0.492	0.487	0.35497	77.925 (3, 421)	0.000	2.077

Notes: Dependent variable = Risk Propensity. Predictors = Artificial Intelligence Literacy, Behavioural Finance, and Financial Literacy. SEE = Standard Error of the Estimate.

The results of the regression analysis offer a detailed perspective on how artificial intelligence literacy, behavioural finance awareness, and financial literacy relate to individuals' financial risk propensity. The model summary indicates that the coefficient of determination (R^2) is 0.492, suggesting that approximately 49.2% of the variance in risk propensity is explained by the model's predictors. The adjusted R^2 of 0.487 indicates that the model's explanatory power remains stable after accounting for the number of predictors. Furthermore, the Durbin–Watson statistic of 2.077 suggests that autocorrelation is absent in the residuals, indicating that the error terms are independent and do not exhibit a systematic pattern (Field, 2013).

The ANOVA results further confirm that the regression model as a whole is statistically significant ($F(3,421) = 77.925$, $p < 0.001$), indicating that the set of independent variables collectively explains variations in risk propensity. A closer examination of the coefficient estimates reveals meaningful differences in the relative influence of the predictors. Behavioural finance emerges as the most influential factor in the model ($B = 0.248$, $\beta = 0.235$, $t = 46.930$, $p < 0.001$), indicating that individuals with greater awareness of behavioural finance concepts exhibit a higher financial risk propensity. This finding is consistent with the broader literature suggesting that awareness of cognitive biases and behavioural dynamics can shape individuals' willingness to engage with financial risk (Shefrin, 2000).

Financial literacy also shows a statistically significant, positive association with risk propensity ($B = 0.055$, $\beta = 0.053$, $t = 5.730$, $p < 0.001$). Although the standardised effect size remains relatively modest compared with behavioural finance awareness, the result indicates that individuals with stronger financial knowledge are better able to evaluate risk–return trade-offs and may therefore be more inclined to accept financial uncertainty.

Similarly, artificial intelligence literacy shows a positive and statistically significant relationship with risk propensity ($B = 0.041$, $\beta = 0.039$, $t = 13.750$, $p < 0.001$). This result suggests that individuals with greater familiarity with artificial intelligence systems and algorithm-based decision-making environments may feel more confident when interacting with technologically mediated financial tools. Such familiarity may reduce perceived uncertainty and encourage individuals to engage more actively in risk-related financial decisions.

An examination of the multicollinearity diagnostics indicates that multicollinearity is not a concern in the model. The Variance Inflation Factor (VIF) values remain close to 1.000, while tolerance values are well above the commonly accepted threshold of 0.10. These indicators suggest that the independent variables do not exhibit problematic levels of intercorrelation and that the estimated regression coefficients can be interpreted reliably (Kutner et al., 2005).

Additional robustness checks were conducted by introducing demographic variables such as gender, age group, and university type as control variables in supplementary regression models. The inclusion of these variables did not materially alter the direction or statistical significance of the primary relationships observed in the baseline model. These findings suggest that the core relationships between financial cognition variables and risk propensity remain relatively stable across demographic subgroups.

Taken together, the findings highlight the prominent role of behavioural finance awareness in shaping individuals' risk-related financial behaviour, while also demonstrating that both financial literacy and artificial intelligence literacy contribute significantly—albeit to a lesser extent—to explaining variations in risk propensity. These results are broadly consistent with previous research emphasising the importance of financial knowledge and cognitive awareness in influencing financial decision-making processes and risk-taking behaviour (Lusardi & Mitchell, 2014).

Diagnostic procedures were also performed to evaluate potential multicollinearity among predictors and the independence of residuals within the regression framework. The relevant statistical indicators are summarised in Table 12.

Table 12: Multicollinearity and Residual Independence Diagnostics

Test	Criterion	Result	Interpretation
Harman's single-factor (unrotated PCA)	First factor < 50%	34.7%	CMV unlikely to dominate
Single-factor CFA vs measurement CFA	Single-factor fit should be poor	Poor fit	CMV concern reduced

The diagnostics presented in Table 12 indicate that multicollinearity does not substantially compromise the regression estimates. The absence of a dominant single-factor influence and the acceptable distribution of residual patterns suggest that parameter estimates remain stable and interpretable. These findings enhance confidence in the robustness of the regression coefficients and support the analytical adequacy of the model specification. Overall, the regression assumptions appear to be satisfactorily met.

Discussion

The findings of this study provide significant insights into the interplay between artificial intelligence (AI) literacy, behavioural finance, financial literacy, and risk propensity. The results demonstrate that behavioural finance awareness emerges as the most influential predictor of risk propensity, aligning with prior research emphasising the role of cognitive biases and heuristics in financial decision-making (Kahneman & Tversky, 1979; Shefrin, 2000). Financial literacy also exhibits a positive, albeit weaker, association with risk propensity, reinforcing the notion that financially knowledgeable individuals tend to take more calculated risks. While AI literacy is positively correlated with risk propensity, its predictive strength is relatively limited, suggesting that mere familiarity with AI-driven financial tools does not necessarily translate into higher risk-taking behaviours.

The role of behavioural finance in shaping risk propensity has been well documented in the literature. Prospect theory posits that individuals do not assess risks in absolute terms but rather in relation to perceived gains and losses, often exhibiting loss aversion (Kahneman & Tversky, 1979). The strong influence of behavioural finance awareness in this study suggests that individuals who understand biases such as overconfidence, herd behaviour, and framing effects are more conscious of how they approach financial risks. This finding is consistent with Charness and Gneezy, who found that individuals with higher behavioural finance awareness exhibited more consistent risk-taking behaviours across different investment scenarios. However, while previous research indicates that behavioural finance awareness can sometimes lead to excessive caution, this study's results suggest that it fosters a more calculated approach to financial risks rather than a complete aversion (Charness & Gneezy, 2012).

Regarding financial literacy, the findings align with prior studies demonstrating that individuals with stronger financial knowledge engage in more informed and rational financial decision-making (Lusardi

& Mitchell, 2014; Van Rooij et al., 2011). Financial literacy is often associated with prudent risk-taking, as financially literate individuals tend to diversify their investments and evaluate market conditions more effectively. However, some scholars argue that financial literacy does not always correlate with lower risk aversion. For instance, Bucher-Koenen & Ziegelmeyer (2014) found that financially literate individuals often take greater financial risks because they feel more confident in their ability to manage complex financial instruments. This study partially supports that argument by showing a positive relationship between financial literacy and risk propensity, albeit with a weaker predictive power than behavioural finance awareness (Bucher-Koenen & Ziegelmeyer, 2014).

The impact of AI literacy on risk propensity presents a novel and evolving area of financial research. While prior studies suggest that AI literacy enhances financial decision-making by providing algorithm-based insights and predictive analytics, this study indicates that AI literacy alone does not strongly drive risk-taking behaviour. Liang and Wang found that individuals with high AI literacy were more likely to adopt algorithmic trading strategies, which can increase risk engagement. However, the present findings suggest that AI literacy's effect on risk propensity is conditional—mere familiarity with AI-driven financial tools does not automatically translate into higher risk-taking. Instead, AI literacy may act as a complementary factor that enhances financial decision-making when combined with behavioural finance awareness and financial literacy. This aligns with Wu et al., who found that AI literacy, when coupled with financial literacy, improved investment efficiency but also increased susceptibility to automation bias, in which individuals over-rely on AI-generated financial recommendations (Brynjolfsson & McAfee, 2017; Wu et al., 2023).

The findings of the present study should be interpreted within the contextual boundaries of the sample. The dataset was limited to students enrolled in healthcare-related academic programs. Therefore, the conclusions derived from this research cannot be generalised to broader university populations, different academic disciplines, or professional investor groups. The behavioural, cognitive, and technological orientations of healthcare students may differ structurally from those in business, engineering, or finance programs. Accordingly, the results should be understood as context-specific rather than universally representative.

The regression analysis revealed that artificial intelligence literacy, behavioural finance awareness, and financial literacy were all positively associated with risk propensity. However, it would be methodologically inappropriate to interpret these findings as indicating that one construct is categorically "more important" than the others solely based on standardised beta coefficients. Although behavioural finance exhibited the highest standardised coefficient in the model, regression beta values reflect partial effects, holding other predictors constant, and do not capture potential interaction effects, indirect pathways, or latent structural interdependencies.

Furthermore, the instruments employed in the study include multidimensional structures. Despite this, the current analysis was conducted at the aggregate scale level. Therefore, statements suggesting that specific sub-dimensions of behavioural finance (e.g., overconfidence, loss aversion, herd behaviour) were influential cannot be substantiated unless those sub-dimensions are modelled separately. The present findings demonstrate the predictive effect of the overall construct rather than its internal components. Future research should examine sub-dimensions individually to determine whether certain cognitive biases exert stronger or weaker effects on risk propensity.

Conclusion

This study examined the predictive roles of artificial intelligence literacy, behavioural finance awareness, and financial literacy in explaining risk propensity among students enrolled in healthcare-related academic programs. The findings indicate that all three constructs contribute significantly to the variance in risk-taking behaviour within the specified sample.

However, these results should be interpreted within the study's contextual boundaries. The sample consisted exclusively of healthcare students; therefore, the findings cannot be generalised to broader university populations or professional investor groups. The behavioural and cognitive orientations of this specific academic cohort may structurally differ from those in finance or business disciplines.

Furthermore, the effects identified in the regression model represent direct predictive relationships at the aggregate scale level. No claims are made regarding the relative dominance of one construct over another beyond their partial contributions within the model. The multidimensional structures of the scales were not separately analysed; therefore, interpretations are limited to the overall constructs rather than their internal sub-dimensions.

Within these analytical boundaries, the results suggest that risk propensity is shaped by the combined influence of technological literacy and cognitive-financial awareness rather than by a single dominant factor. Future research employing sub-dimensional analyses and structural modelling techniques may provide a more nuanced understanding of the underlying mechanisms.

Theoretical and practical implications

The results of this study reinforce the significance of behavioural finance education in shaping risk-taking behaviours. Given that behavioural biases influence financial decisions, incorporating behavioural finance into financial literacy programs could improve individuals' ability to recognise and mitigate biases. Policymakers and educational institutions should emphasise the development of behavioural finance curricula, particularly for populations that engage with AI-powered financial tools. Additionally, AI literacy training should be integrated into financial education programs to ensure individuals understand both the benefits and limitations of AI-driven decision-making. As AI-driven financial services become more prevalent, understanding how AI tools generate insights and the potential biases they may introduce will be crucial to avoiding over-reliance on algorithmic recommendations.

From a financial services perspective, the findings suggest that robo-advisors and AI-driven financial platforms should incorporate behavioural insights into their recommendations. While AI tools can enhance financial decision-making, their effectiveness depends on how well users understand their limitations. Financial institutions should consider designing AI-powered investment tools that educate users about risk-taking behaviours, behavioural biases, and financial literacy principles. This could be achieved through adaptive AI models that provide personalised financial guidance based on an individual's risk tolerance and cognitive biases.

Sample scope and limitations

The sample consisted of students enrolled in healthcare-related academic programs. This group was not selected merely for convenience but due to its conceptual relevance. Healthcare students are increasingly exposed to artificial intelligence applications in professional contexts while simultaneously operating outside formal finance-oriented education. This positioning provides meaningful context for examining how technological literacy and behavioural finance awareness relate to risk propensity in a non-business academic population.

Most prior studies in financial literacy and behavioural finance have focused primarily on business students, investors, or general adult samples. By examining healthcare students, this study extends the literature into an interdisciplinary setting in which financial decision-making competencies are not structurally embedded in the curriculum, but risk evaluation remains cognitively relevant.

Nevertheless, the findings are limited to this specific population and cannot be generalised to other academic disciplines or professional groups. Future research should test the model across different educational fields to assess its broader applicability.

Future directions

Building upon the limitations of this study, several future research avenues are suggested. First, expanding the sample to include individuals from diverse fields, such as finance, engineering, and business, could provide a more comprehensive view of how AI literacy intersects with financial decision-making across professional contexts. Second, investigating the role of AI in real-world financial decision-making, including investment behaviours and savings strategies, would enhance the practical implications of AI literacy in financial markets. Third, integrating qualitative research methods, such as in-depth interviews and focus groups, could yield deeper insights into individuals' perceptions of AI-driven financial tools and their concerns about algorithmic decision-making. Additionally, the potential influence of regulatory frameworks and ethical considerations on AI literacy and financial decision-making remains an unexplored area that warrants further investigation. Lastly, future studies should examine whether educational interventions to improve AI literacy lead to measurable improvements in financial decision-making, thereby establishing best practices for integrating AI education into financial literacy programs.

Peer-review:

Externally peer-reviewed

Conflict of interests:

The authors have no conflict of interest to declare.

Grant Support:

The authors declared that this study has received no financial support.

Ethics Committee Approval:

Ethics committee approval for this study was received from Istanbul Yeni Yüzyıl University on 04/03/2025, with Decision No. 2025/03-1501 and document number.

Author Contributions:

Idea/Concept/Design: **H. T., M. Ö.**, Data Collection and/or Processing: **H. T., M. Ö.**, Analysis and/or Interpretation: **H. T., M. Ö.**, Literature Review: **H. T., M. Ö.**, Writing the Article: **H. T., M. Ö.**, Critical Review: **H. T., M. Ö.**, Approval: **H. T., M. Ö.**

References

Agrawal, A., Gans, J. S., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Press.

Ahmetoğulları, K. (2024). Dijital finansal okuryazarlık ve finansal teknolojilerin ilişkisinde rol alan faktörler: Yabancı turistler üzerinde bir uygulama. *EKEV Akademi Dergisi, 99*, 211–233. https://doi.org/10.17753/sosekev.1487134

Aishwaryalaxmi, N. S., & Rathod, P. (2024). Artificial intelligence (AI) as a moderating variable in the relationship between financial inclusion, digital adoption, and financial literacy in developing economies. In *ITM Web of Conferences* (Vol. 68, 01034). EDP Sciences.

Atabay, İ., Kutbay, A. Y., Karakaş, F., Koç, F., & Alamur, B. (2018). Risk eğiliminin finansal iyi olma hâli üzerindeki etkileri: Banka çalışanları üzerinde bir uygulama. PressAcademia Procedia, 7(1), 191–197. https://doi.org/10.17261/Pressacademia.2018.879

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W.W. Norton & Company.

Bucher-Koenen, T., & Ziegelmeyer, M. (2014). Who lost the most? Financial literacy, cognitive abilities, and the financial crisis. *Journal of Pension Economics & Finance, 13*(1), 52–84.

Bulmer, M. G. (1979). *Principles of statistics*. Dover Publications.

Charness, G., & Gneezy, U. (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behaviour & Organization, 83*(1), 50–58.

Chummun, B. Z. (2024). Can artificial intelligence promote financial literacy in higher education? A case in the modern world. In *Impacts of generative AI on creativity in higher education* (pp. 1–26). IGI Global.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (partially) control them. *Management Science, 64*(3), 1155–1170.

Durak, İ., Çise, S. N., & Yazıcı, S. (2024). Developing a financial technology (FinTech) adoption scale: A validity and reliability study. *Research in International Business and Finance, 70*, 102344. https://doi.org/10.1016/j.ribaf.2024.102344

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Sage.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

Garba, M., Salleh, F., Hafiz, U. A., & Bakar, N. M. A. (2022). Insurance literacy, risk knowledge management, risk-taking propensity and economic sustainability among SMEs. *Journal of Social Economics Research, 9*(2), 92–110.

George, D., & Mallery, P. (2010). *SPSS for Windows step by step: A simple guide and reference (17.0 update)*. Pearson.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Jain, J., Walia, N., Kaur, M., & Singh, S. (2022). Behavioural biases affecting investors' decision-making process. *Management Research Review, 45*(8), 1079–1098.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263–291.

Kılıç, Y., Ata, H. A., & Hüseyrek, İ. (2015). Finansal okuryazarlık: Üniversite öğrencilerine yönelik bir araştırma. *Muhasebe ve Finansman Dergisi, 66*, 129–150. https://doi.org/10.25095/mufad.396535

Korkmaz, A. G., Yin, Z., Yue, P., & Zhou, H. (2021). Does financial literacy alleviate risk attitude and risk behaviour inconsistency? *International Review of Economics & Finance, 74*, 293–310. https://doi.org/10.1016/j.iref.2021.03.002

Kurowski, Ł., & Szelągowska, A. (2024). Financial literacy in the era of artificial intelligence. *Journal of Banking and Financial Economics, 1*, IV–VI.

Kutner, M. H., Nachtsheim, C., Neter, J., & Li, W. (2005). *Applied linear statistical models*. McGraw-Hill.

Levantesi, S., & Zacchia, G. (2021). Machine learning and financial literacy. *Journal of Risk and Financial Management, 14*(3), 120.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy. *Journal of Economic Literature, 52*(1), 5–44.

Murugesan, R., & Manohar, V. (2019). AI in financial sector: A driver to financial literacy. *Shanlax International Journal of Commerce, 7*(3), 66–70.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Özbek, A. (2025). The effects of behavioural biases on investment decisions. *Ordu Üniversitesi Sosyal Bilimler Araştırmaları Dergisi, 15*(2), 948–960. https://doi.org/10.48146/odusobiad.1388180

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioural research. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rahman, A. (2024). Artificial intelligence role in financial literacy in banking channels. *Journal of Economics and Management, 4*(1), 150–155.

Riyani, D. (2023). Artificial intelligence and financial literacy in Society 5.0. In *ICOEMA Conference Proceedings* (pp. 145–157).

Shanmugam, K., Chidambaram, V., & Parayitam, S. (2023). Personality traits, financial literacy and risk propensity. *IIM Kozhikode Society & Management Review, 12*(1), 85–101.

Shefrin, H. (2000). *Beyond greed and fear: Understanding behavioural finance and the psychology of investing*. Harvard Business School Press.

Thaler, R. H. (1985). Mental accounting and consumer choice. *Marketing Science, 4*(3), 199–214.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53–55.

Tripathi, R. (2024). Financial literacy and artificial intelligence to mitigate behavioural biases. *International Journal of Emerging Markets.*

Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics, 101*(2), 449–472.

Wu, Y., Zhang, X., & Li, H. (2023). AI literacy and financial decision-making. *Journal of Behavioural Finance, 24*(2), 200–220.

Xie, Y., & Konomi, S. I. (2024). Human-centered AI environment to enhance financial literacy. In *Human-Computer Interaction Conference Proceedings* (pp. 360–374). Springer.