Article

SciPap
scientific papers

Embracing Intelligent Insights: Unveiling Investor Adoption of AI Advice and Risk Appetite

Scientific Papers of the University of Pardubice, Series D: Faculty of Economics and Administration
2025, 33(1), 2136.

DOI: 10.46585/sp33012136
editorial.upce.cz/SciPap

Hang Dang Thi Thu

HCMC University of Foreign Languages - Information Technology, Ho Chi Minh City, Vietnam

Sandeep Kumar Dey

Tomas Bata University in Zlín, Faculty of Management and Economics, Czechia

Sinh Duc Hoang

International University, School of Business, Ho Chi Minh City, Vietnam

Vietnam National University, Ho Chi Minh City, Vietnam

Abstract

This paper aims to reveal the factors influencing investors' intention to accept AI advice in financial decision-making. By integrating the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM), it proposes a comprehensive model that elucidates the intricate relationships between social norms, attitude, perceived behavioral control, and the intention to accept AI advice, with a particular focus on examining risk tolerance as a moderating factor. A questionnaire survey was conducted with 569 Vietnamese investors to collect data in three different times. Partial least squares structural equation modeling (PLS-SEM) was utilized to analyze the measurement model and test the hypotheses. Results indicate that perceived usefulness, perceived ease of use, attitude, subjective norms, and perceived behavioral control positively influence the intention to accept AI advice. Furthermore, risk tolerance significantly moderates the link between attitude, subjective norms, perceived behavioral control, and intention to accept AI advice. This pioneering study introduces a comprehensive model unveiling the dynamics of AI advice acceptance in finance. It explores the novel concept of risk tolerance as a moderator, marking an important step in understanding human-AI interaction for financial decisions. Findings provide valuable insights into evolving AI adoption, especially in high-risk contexts.

Keywords

AI advice, Risk tolerance, TAM, TPB, Financial decision-making

JEL Classification

G4, G11, G15

Introduction

Artificial Intelligence (AI) has rapidly evolved from a futuristic concept into an essential component of modern life, influencing industries ranging from healthcare and education to finance and entertainment. The global AI market, valued at $27.23 billion in 2019, is projected to exceed $267 billion by 2027, underscoring its exponential growth and widespread adoption across various sectors (Fortune Business Insights, 2022). AI-driven innovations have transformed decision-making processes, enhanced efficiency and providing sophisticated analytical capabilities. From autonomous vehicles making split-second navigation decisions (Liu et al., 2020) to AI-powered diagnostic tools that outperform human doctors in detecting diseases (Kumar et al., 2022). AI has demonstrated its ability to process vast amounts of data and offer reliable recommendations. In the financial sector, AI-driven algorithms have significantly influenced trading, investment management, and risk assessment, with robo-advisors offering automated, data-driven investment recommendations designed to assist individuals in making informed financial decisions. However, despite the rapid advancement and demonstrated effectiveness of AI-driven financial tools, many investors remain hesitant to embrace AI-generated financial advice. Traditional financial decision-making has been heavily reliant on human judgment, personal experience, and expert consultation. The reluctance to trust AI-generated investment recommendations stems from concerns related to trust, transparency, perceived

Corresponding author:
Sinh Duc Hoang, International University, School of Business, Ho Chi Minh City, Vietnam
Email: hdsinh@hcmiu.edu.vn

accuracy, and risk tolerance, all of which play a crucial role in determining the adoption of AI in financial decision-making.

While AI has been successfully integrated into low-risk applications such as personalized shopping recommendations (Ashoori & Weisz, 2019) and news curation (Diakopoulos & Koliska, 2017), its acceptance in high-stakes domains such as finance, healthcare, and legal decision-making remains an ongoing debate. AI-driven financial recommendations involve substantial financial risk, making trust in the technology a critical factor for adoption. Research on AI acceptance in finance has yielded mixed results. While some investors appreciate the efficiency, objectivity, and data-driven nature of AI financial recommendations, others express skepticism regarding AI's ability to adapt to dynamic market conditions and its potential limitations in handling unpredictable economic downturns (Miziołek, 2021). Previous studies have predominantly examined AI acceptance through technology adoption models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which emphasize factors such as perceived usefulness, ease of use, and social influence. However, when applied to AI-driven financial decision-making, these models fail to fully capture the complexities involved in AI acceptance, particularly in high-risk financial contexts.

Despite the increasing integration of AI into financial decision-making, critical gaps remain in understanding the factors that influence investor acceptance of AI-generated financial advice. First, the psychological mechanisms driving investors' willingness to rely on AI recommendations have not been sufficiently examined. While traditional technology adoption models emphasize usability and perceived benefits, they fail to fully capture the cognitive and emotional dimensions that shape investment decisions. Financial decision-making inherently involves uncertainty, emotional influences, and cognitive biases, all of which affect how investors perceive and evaluate AI-driven advice. A more comprehensive understanding of how attitudes, perceived behavioral control, and subjective norms influence the intention to adopt AI financial advice is essential for advancing research in this domain. Second, the role of risk tolerance in shaping AI acceptance has been largely overlooked. Given the inherent variability of risk in financial decision-making, investors with different levels of risk tolerance may respond differently to AI-generated recommendations. While some may view AI as a rational, data-driven tool that mitigates risk by providing objective insights, others particularly those with lower risk tolerance may remain skeptical of AI’s ability to navigate market volatility and account for unpredictable financial disruptions (Singh Channe, 2024). Despite the growing scholarly interest in the intersection of AI and investment behavior, research has yet to explore how risk tolerance moderates the relationships between psychological factors such as attitudes, trust, and perceived accuracy in influencing AI acceptance.

To address these research gaps, this study integrates the Theory of Planned Behavior (TPB) (Ajzen, 1985) with the Technology Acceptance Model (TAM) to develop a comprehensive framework that explains investors’ intention to accept AI-driven financial advice. The TPB suggests that human behavior is influenced by attitudes, subjective norms, and perceived behavioral control, all of which play a vital role in shaping decision-making processes. By incorporating TAM’s emphasis on perceived usefulness and ease of use, this study develops a holistic model that accounts for both the technological and psychological dimensions of AI acceptance. Specifically, this research investigates the relationships between attitudes toward AI financial advice, subjective norms, and perceived behavioral control in influencing investors' willingness to rely on AI-generated recommendations. Moreover, this study introduces risk tolerance as a moderating factor, examining how an individual’s propensity for risk influences their likelihood of accepting AI-driven financial advice.

By empirically testing this framework, this study aims to contribute to the growing body of research on AI adoption in finance while providing practical insights for financial institutions, AI developers, and policymakers. First, this research bridges the gap between AI adoption studies and behavioral finance by examining the cognitive and psychological factors that shape investor decisions. Existing studies often focus on the technical capabilities of AI without considering the emotional and behavioral aspects that influence adoption. Second, this study introduces risk tolerance as a key moderating factor, recognizing that AI acceptance is not a binary decision but rather a process influenced by individual risk preferences. Unlike previous models that assume AI acceptance is uniform across users, this study explores how risk tolerance can amplify or diminish an investor’s willingness to integrate AI-driven tools into their decision-making process. Third, by integrating TAM and TPB, this study offers a robust theoretical framework that extends beyond the financial sector, providing insights into AI adoption in other high-risk decision-making environments such as healthcare and legal AI applications.

From a practical standpoint, understanding the factors that drive AI acceptance in financial decision-making can help financial institutions and AI developers design more effective AI-driven investment advisory systems. By recognizing the importance of trust, perceived control, and risk tolerance, firms can develop AI tools that align with investor preferences, enhance transparency, and foster greater confidence in AI-generated recommendations. Additionally, policymakers can leverage these findings to establish regulatory frameworks that promote ethical AI adoption, ensuring that AI-driven financial tools are designed with user trust and fairness in mind.

Literature Review

Related Works
The increasing integration of Artificial Intelligence (AI) in financial decision-making has generated widespread debate regarding its acceptance, with user responses ranging from automation bias to AI aversion (Dietvorst et al., 2015; Tomsett et al., 2020; Wickramasinghe et al., 2020). Automation bias refers to a tendency where users overly rely on AI-generated recommendations, assuming their accuracy without conducting independent verification (Parasuraman & Manzey, 2010). Conversely, AI aversion reflects a reluctance to adopt AI-driven recommendations, often due to skepticism regarding the accuracy, transparency, or adaptability of AI-based decision-making models (Tomsett et al., 2020). Several studies indicate that automation bias is more prevalent in structured, logic-based tasks, whereas AI aversion is more pronounced in subjective decision-making contexts, such as investment and healthcare choices (Gaudiello et al., 2016; Logg, 2017).
The existing literature identifies three principal categories of factors influencing AI acceptance: system characteristics, user characteristics, and contextual factors (Rzepka & Berger, 2018). Research has demonstrated that higher transparency in AI decision-making increases trust and enhances acceptance (Yu & Li,2022). However, studies also show that overly autonomous AI systems that mimic human-like decision-making behaviors can trigger psychological discomfort and resistance among users (Złotowski et al., 2017). Additionally, the alignment between users' cognitive models and AI system presentation significantly impacts adoption rates (Shmueli et al., 2016), while demographic congruence between users and AI avatars has been shown to positively influence AI acceptance in decision-making tasks (Qiu & Benbasat, 2010).

Given that commercial AI-driven financial advisory systems are often proprietary and opaque to protect intellectual property, system characteristics are not the focus of this study (Lee et al., 2021). Instead, this research examines user characteristics and contextual factors, specifically investigating the role of attitude, subjective norms, perceived behavioral control, and risk tolerance in shaping investors’ acceptance of AI-generated financial advice.

Technology Acceptance Model and Attitude toward AI
Attitude has been widely recognized as a key determinant of technology adoption and behavioral intention, as highlighted in both the TAM (Davis, 1989) and the TPB (Ajzen, 1991). Attitude refers to an individual's overall evaluation of a given technology, encompassing perceived benefits, risks, and trust in its functionality (Binh et al., 2024; Hoang et al., 2023). Numerous empirical studies have demonstrated that a positive attitude toward AI technology is associated with higher acceptance rates in various domains, including healthcare (Kelly et al., 2023) consumer decision-making (Chong et al., 2022), and financial advisory services (Yang & Lee, 2024)

Within the TAM framework, perceived usefulness (PU) and perceived ease of use (PEU) are established as the primary drivers of attitude formation toward new technologies (Davis, 1989; Venkatesh & Davis, 2000). Perceived usefulness refers to the extent to which an individual believes that AI enhances their ability to make financial decisions, whereas perceived ease of use pertains to how effortless users perceive AI tools to be in executing tasks (Davis, 1989). Empirical research has consistently found that users who perceive AI-driven financial tools as beneficial in improving investment decision-making, efficiency, and risk assessment exhibit stronger positive attitudes toward AI (Riedel et al., 2022). Additionally, studies on AI adoption in e-commerce and financial technology services demonstrate that perceived ease of use significantly influences acceptance by reducing perceived cognitive effort and enhancing the user experience (Madanchian, 2024; Sadriwala & Sadriwala, 2022). AI adoption is particularly high when systems are perceived as intuitive, transparent, and requiring minimal learning effort (Sukandar & Hermawan, 2022).

Based on these empirical insights, the following hypotheses are proposed:

H1: Perceived usefulness has a positive impact on attitude toward AI.

H2: Perceived ease of use positively impacts attitude toward AI.

Theory of Planned Behavior in AI Adoption
According to the Theory of Planned Behavior (TPB) (Ajzen, 1991), an individual’s intention to engage in specific behavior is determined by three key factors: attitude toward the behavior, subjective norms, and perceived behavioral control (PBC). These components influence decision-making by shaping individuals' expectations about the outcomes, perceived social pressures, and confidence in their ability to perform the behavior. TPB has been extensively applied in technology adoption research, providing a comprehensive framework for understanding the psychological and social factors influencing the acceptance of new technologies, including AI-driven financial advisory systems (Venkatesh et al., 2003). Drawing from TPB, this study examines how attitude, subjective norms, and perceived behavioral control influence investors’ intention to accept AI-generated financial advice.

Subjective norms refer to the perceived social expectations regarding whether an individual should engage in a particular behavior (Ajzen, 1991). In the context of AI-driven financial decision-making, subjective norms represent the influence of peers, financial advisors, institutional investors, and professional networks on an individual’s willingness to use AI-generated investment advice. Given that financial decisions often involve risk and uncertainty, individuals frequently seek validation and guidance from trusted sources before committing to investment choices (Nguyen et al., 2016).

Empirical studies have demonstrated that social influence plays a crucial role in shaping the adoption of AI-based financial tools. Investors who perceive that respected figures within their financial or professional networks endorse AI-powered financial advisors are more likely to view these tools as reliable and trustworthy (Northey et al., 2022). For example, research has shown that when financial institutions promote AI-powered robo-advisors as essential tools for modern investment strategies, investors are more inclined to integrate them into their decision-making processes (Ben-David et al., 2021). Similarly, the growing use of AI in financial analysis by hedge funds and institutional investors signals a broader industry shift toward AI-driven investment strategies, influencing individual investors to align with emerging financial norms (Yao, 2024).

Moreover, subjective norms are reinforced through observational learning and social conformity, whereby investors adjust their behavior based on the perceived approval or disapproval of their social environment (Rimal, 2003). This aligns with research in behavioral finance, which suggests that investors are more likely to adopt AI-powered advisory tools if they see others in their peer group benefiting from AI-driven financial recommendations (Zhu et al., 2024). Given the increasing institutional acceptance of AI in investment management, it is expected that subjective norms will positively influence investors' intentions to accept AI-generated financial advice.

Perceived behavioral control (PBC) refers to an individual's confidence in their ability to perform a specific behavior based on perceived ease or difficulty (Ajzen, 1991). Within the context of AI adoption in financial decision-making, PBC reflects an investor's perception of their ability to understand, navigate, and effectively utilize AI-powered investment tools. Higher perceived behavioral control increases the likelihood of AI adoption, as individuals who feel competent and confident in their ability to engage with AI technology are more willing to integrate it into their decision-making processes (Jiao & Cao, 2024).

Several studies have highlighted the role of digital literacy and financial self-efficacy in determining perceived behavioral control over AI-based financial advisory tools. Investors who are familiar with AI applications, digital platforms, and algorithmic trading are more likely to perceive AI-generated recommendations as beneficial and manageable (Gupta & Singh, 2024). Conversely, investors with limited exposure to AI-driven investment tools or lower confidence in their ability to interpret algorithmic outputs may develop resistance to AI adoption due to concerns about complexity and lack of control (Horowitz et al., 2023).

Moreover, transparency and user-friendliness play a crucial role in shaping perceived behavioral control. When AI-driven financial advisory systems are designed with intuitive interfaces, clear explanations, and transparent decision-making processes, investors are more likely to feel empowered and in control of their financial choices (Addy et al., 2024; Venkatesh & Davis, 2000). In contrast, AI systems that operate as "black-box" models, where the rationale behind investment recommendations is opaque, can reduce perceived behavioral control, leading to greater resistance toward AI adoption (Huynh, 2024).

Attitude toward AI is a fundamental determinant of technology adoption, representing an individual's overall evaluation of AI-based financial tools, including perceptions of their usefulness, reliability, and effectiveness (Ajzen, 1991). Positive attitudes toward AI have been shown to increase the likelihood of technology acceptance across various domains, including e-commerce (Phan et al., 2025), healthcare (Cheng et al., 2022), and financial technology services (Ho,2023).

Several studies suggest that trust and perceived accuracy significantly influence attitudes toward AI-driven financial advisory tools. Investors who perceive AI-generated financial recommendations as accurate, data-driven, and free from human bias tend to develop stronger positive attitudes toward AI adoption (Jacobsen et al., 2020; Schaffer et al., 2015). Additionally, AI's ability to process large volumes of financial data and generate objective investment strategies enhances investors' confidence in its capabilities, further reinforcing a favorable attitude toward AI-based financial decision-making (Riedel et al., 2022).

Conversely, negative attitudes toward AI can arise from concerns about transparency, algorithmic accountability, and the potential for biases in AI-driven decision-making (Araujo et al., 2020). Investors who view AI as a "black-box" system that lacks interpretability and human oversight may develop skepticism regarding its effectiveness in financial advisory roles (Liang et al., 2021; Ochmann et al., 2021). Furthermore, the perception that AI cannot account for qualitative market factors, such as geopolitical events or industry-specific nuances, may contribute to negative attitudes toward AI adoption (Longoni et al., 2019).

Accordingly, the following hypotheses are formulated:

H3: Attitude has a positive impact on the intention to accept AI advice in financial decision-making.
H4: Subjective norms toward AI have a positive impact on the intention to accept AI advice.
H5: Perceived behavioral control has a positive impact on the intention to accept AI advice in financial decision-making.

The Moderating Role of Risk Tolerance

Risk tolerance refers to an individual's willingness and ability to endure financial uncertainty in pursuit of potential returns. It is a fundamental psychological and behavioral trait that influences investment decision-making, financial planning, and portfolio management (Loewenstein et al., 2001). Risk tolerance is shaped by both cognitive and emotional factors, including financial knowledge, past investment experiences, personality traits, and economic conditions (Bao et al., 2022). Investors with high risk tolerance are more likely to engage in volatile, high-return investments, such as stocks, cryptocurrencies, or speculative assets, while those with low risk tolerance prefer stable, low-risk assets, such as bonds, fixed deposits, or blue-chip stocks (Nam et al., 2023). Additionally, risk tolerance varies across individuals and can change over time, depending on market conditions, personal financial goals, and life circumstances (Flavián et al., 2021). Understanding risk tolerance is essential for financial advisors, AI-driven investment platforms, and policymakers to develop tailored financial strategies that align with investors' preferences and risk-taking capacities.

Drawing from the TPB (Ajzen, 1991), we argue that when risk tolerance is high, investors are more likely to develop positive attitudes toward AI-driven financial advisory tools, as they perceive AI as an opportunity to enhance investment decision-making through data-driven insights, automation, and predictive analytics. High-risk tolerance investors are typically more open to innovation, willing to explore new investment technologies, and less concerned about potential AI-related uncertainties (Flavián et al., 2021). They may view AI-generated recommendations as efficient mechanisms for maximizing returns, capitalizing on algorithmic strategies that reduce emotional biases and optimize decision-making in volatile markets (Capponi et al., 2019). Moreover, subjective norms may exert a stronger influence on high-risk tolerance investors, as they tend to align their behaviors with emerging financial trends, peer endorsements, and institutional adoption of AI-based investment tools (Bao et al., 2022). Furthermore, perceived behavioral control is likely to be higher among risk-tolerant investors, as they are more confident in their ability to navigate AI platforms, experiment with algorithmic decision-making, and integrate AI insights into their financial strategies (Longoni et al., 2019).

On the contrary, when risk tolerance is low, investors are more likely to develop negative attitudes toward AI-driven financial advisory tools, as they perceive algorithmic decision-making as unpredictable, opaque, and incapable of incorporating qualitative financial factors such as market sentiment, regulatory changes, or industry-specific developments (Nam & Hwang, 2023). Risk-averse investors may have a stronger preference for human financial advisors, believing that personalized, expert-driven insights are more reliable and adaptable than AI-generated recommendations (Longoni et al., 2019). Additionally, subjective norms may have a weaker influence on investors with low risk tolerance, as they prioritize personal risk management strategies over external endorsements and may resist adopting AI simply because others in the financial industry are using it (Bao et al., 2022). Moreover, perceived behavioral control is likely to be lower for risk-averse investors, as they may feel less confident in their ability to interpret AI-generated recommendations, navigate AI-based investment platforms, or trust AI's capacity to manage financial risks effectively (Flavián et al., 2021). Consequently, investors with low risk tolerance may be more resistant to AI adoption, preferring conventional decision-making processes that offer greater perceived security, stability, and human oversight.

H6: Risk tolerance moderates the relationship between attitude toward AI and the intention to accept AI.
H7: Risk tolerance moderates the relationship between subjective norms and the intention to accept AI.
H8: Risk tolerance moderates the relationship between perceived behavioral control and the intention to accept AI.

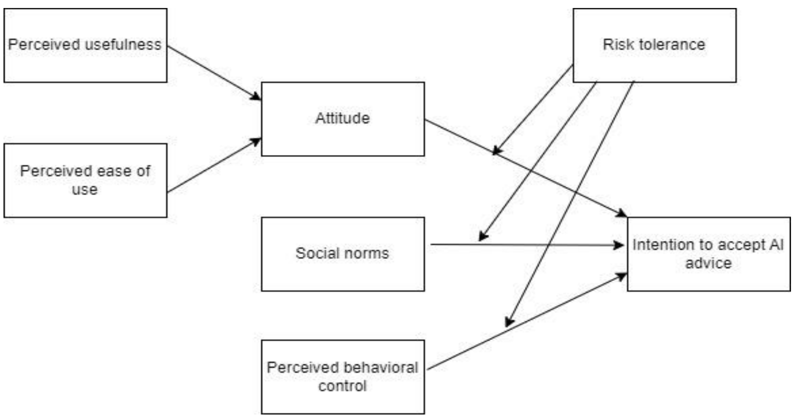

Fig. 1. Empirical model.
Source: own elaboration

Methods

Prior to initiating this study, there were no surveys suitable for measuring the intent to employ AI-based financial advice. As a result, this study has absorbed Venkatesh et al. (2012) scale. Even though the use of questionnaires to collect data is widespread, any measurement that does not satisfy the standards of reliability and validity may cause difficulties in interpreting the results, particularly in empirical studies employing a novel measure, such as the intention to adopt AI advice. We utilized a back-translation strategy to develop a questionnaire to be administered in Vietnamese. An expert in both English and Vietnamese translated the original survey from English to Vietnamese. Then, to guarantee the questionnaire's readability, the Vietnamese version was reviewed by a focus group comprised of professionals with experience adopting AI advice in their field. The authors, who were fluent in Vietnamese and English, then reviewed it thoroughly and corrected any errors. Finally, a Vietnamese-fluent, English-speaking expert translated it back into English. Through our relationship, we then sent invitations via email to potential participants. The operationalization of the used items used a five-point Likert scale with the options "highly disagree" and "highly agree." The Likert five-level scale was used to build the questionnaire because it enables the evaluation of concepts without placing limits on survey participants (Bajdor, 2021).

This study conducted a survey that focused on investors who had experience in AI advice before. A questionnaire has the screening question “Have you ever experienced AI advice before”. If respondents answer “Yes”, they will fill in all the questions below. While respondents answer “No”, the questionnaire is closed. The participants accessed Google Docs questionnaires through desktop computers or mobile devices. Three different surveys were conducted at three different times to minimize any potential common-method bias (Podsakoff, MacKenzie, & Podsakoff, 2012). Investors evaluated the perceived usefulness and usability of AI help in financial decision-making at Time 1. Investors evaluated their attitudes regarding the intention to embrace AI guidance at Time 2—three weeks later. Investors are then asked to rate their risk tolerance, perception of behavioral control, and desire to embrace AI advice in financial decision-making at Time 3, which occurs 3 weeks after Time 2 has passed. We assigned an identification code to each survey so that we could compare replies from different times. The authors distributed 1,000 questionnaires and obtained 872 responses who had experienced AI. After a thorough examination of the returned questionnaires, questionnaires with issues such as missing data and significant discrepancies were discarded. In this round, 569 individuals participated in the survey. This study's sample size exceeds the minimum requirement of 200 respondents for SEM analysis (Hoogland & Boomsma, 1998; Soper, 2022; Westland, 2010) with 397 participants. To avoid the common method variance induced by using perceptual data from the same source, information on these two rounds was collected at two different times from various companies in the Vietnamese aviation industry (Podsakoff et al., 2012).

Table 1. Variables explanation.

	Items	Adapted Sources
Perceived usefulness (PU)	PU1: Using AI advice would improve my performance in managing investments	Venkatesh et al. (2012)
	PU2: Using AI would improve my productivity in managing investments	
	PU3: Using AI advice would enhance my effectiveness in managing investments	
	PU4: I would find AI advice useful in managing investments	
Perceived ease of use (PEU)	PEU1: I would find it easy to manage investments using AI advice	Venkatesh et al. (2012)
	PEU2: It would be easy for me to become skillful at using AI advice	
	PEU3: I would find AI advice easy to use	
Attitude toward AI (ATA)	ATA1: Using AI advice for managing investments seems like a good idea	Venkatesh et al. (2012)
	ATA2: I like the idea of using AI advice for managing personal investments	
	ATA3: Using AI advice for implementing my investments seems like a wise idea	
Subjective norm (SN)	SN1: People who influence my behavior think that I should use the system.	Venkatesh et al. (2012)
	SN2: People who are important to me think that I should use the system	
Perceived behavioral control (PBC)	PBC1: I have control over using AI device system	Venkatesh et al. (2012)
	PBC2: I have the resources necessary to use the system	
	PBC3: Given the resources, opportunities, and knowledge it takes to use the system, it would be easy for me to use the system	
Risk tolerance (RT)	RT1: I can accept AI advice if the chance of getting a good return is great	(Shou & Olney, 2022)
	RT2: I think one has to accept AI advice to gain something	
	RT3: I would like to accept AI advice because the return is too high	
Intention to accept AI advice (IAA)	IAA1: I intend to use AI advice for managing investments	Hoang et al. (2025)
	IAA2: Using AI advice for managing investments is something I would do	
	IAA3: My intention is to use AI advice rather than any human financial advisor	

Results

Descriptive and demographic statistics

As shown in Table 1, 53.08% of the total sample consisted of females. Regarding age, the majority of respondents were aged 26 to 35 (43.06%), followed by those aged 36 to 50 (29.35%).

Table 1. Demographic Characteristics.

Demographic Characteristics		Frequency	Percentage
Gender	Male	267	46.92%
	Female	302	53.08%
Age	18 - 25	50	8.79%
	26 - 35	245	43.06%
	36 - 50	167	29.35%
	51 and above	107	18.80%
Education	Bachelor's degree	195	34.27%
	Master's degree	275	48.33%
	Doctorate degree	99	17.40%
Occupations	Students	115	20.21%
	Self - employment	175	30.76%
	Paid employment	186	32.69%
	Professionals	93	16.34%
Income per month	Below VND 15 million	132	23.20%
	Below VND 30 million	174	30.58%
	Below VND 50 million	161	28.30%
	Above VND 50 million	102	17.93%
Years participated in stock exchange	Below 1 year	102	17.93%
	1 - below 3 years	137	24.08%
	3 year - below 5 years	194	34.09%
	over 5 years	136	23.90%

Most respondents are either paid employment (32.69%) or self-employment (30.76%). Most respondents earned between VND 15 million to below VND 30 million (30.58%), followed by those who earned VND 30 million to below VND 50 million (28.30%) and those who earned below VND 15 million per month (23.20%). In addition, 34.09% percent of respondents said they have participated in the stock exchange from 3 years to below 5 years, while 24.08% of respondents had experience in 1 year to below 3 years. Consecutively, 17.93% of respondents had experience below 1 year and 23.90 % had experience over 5 years.

Table 2. Descriptive statistics of the questionnaire items.

Item	Mean	Median	Standard deviation
PU1	3.687	4	0.951
PU2	3.722	4	0.976
PU3	3.684	4	0.929
PU4	3.675	4	0.946
PEU1	3.68	4	1.015
PEU2	3.78	4	1.007
PEU3	3.677	4	0.973
ATA1	3.787	4	1.018
ATA2	3.634	4	1.175
ATA3	3.733	4	1.004

SN1	3.626	4	0.968
SN2	3.742	4	1.011
PBC1	3.736	4	1.048
PBC2	3.754	4	1.016
PBC3	3.75	4	1.022
RT1	4.098	4	0.807
RT2	4.053	4	0.794
RT3	4.042	4	0.842
IAA1	3.721	4	0.984
IAA2	3.888	4	1.05
IAA3	3.763	4	1.009

Data analysis

Statistical analysis: With a sample size of 569 and 7 latent variables and items, partial least squares (PLS) is deemed a suitable method for data analysis (Ooi and Tan, 2016). This method is suitable for small sample sizes, can predict multidimensional constructs, and can simultaneously analyze structural and measurement models (Ooi and Tan, 2016). In addition, PLS-SEM works well with non-normal data. Due to the fact that the p-values for Mardia's multivariate skewness and kurtosis were less than 0.001, the use of PLS-SEM in this study is further supported (Yusif et al., 2020).

Common bias method: Due to the study's cross-sectional design, the potential hazard of common method bias was assessed using procedural and statistical techniques (Leong et al., 2024). Procedurally, respondents were informed that there were no right or incorrect answers, and the confidentiality and anonymity of responses were ensured. For additional confirmation, we conducted the full collinearity test with a random dependent variable and found the highest variance inflation factor (VIF) value to be 1.937%, which is well below the threshold of 3.3% (Kock and Lynn, 2012). Based on the findings, it can be inferred that there was no major contamination of the data by common method bias.

Assessing measurement model: Following Hair et al. (2017), construct reliability and validity must be evaluated during the analysis of the measurement model. Initially, construct reliability was examined using composite reliability (CR) and Dijkstra-rho Henseler's (rh0_A). (Chong et al., 2012; Teo et al., 2015) According to previous research, CR and rho_A values above 0.7 indicated a substantial level of reliability. Consequently, the CR and rh0_A in Table 4 were in the range of 0.759 to 0.927, reaching the 0.7 minimum for both indices. Second, the average variance extracted (AVE) was used to ascertain convergent validity (Libório et al., 2024). In general, AVE should be greater than 0.5 (Hair et al., 2017). All factor loadings were greater than 0.70. In conclusion, the findings confirmed convergent validity for all latent constructions. Thirdly, discriminant validity was assessed utilizing Heterotrait-Monotrait (HTMT) scores and HTMT inference correlation ratios (Hair et al., 2017). In addition, the HTMT inference (using 5000 bootstrapping samples) revealed that both the lower and upper limits of the 99% confidence interval were less than one (Ooi et al., 2020). This demonstrated that each variable was statistically distinct from the others, establishing discriminant validity (Rönkkö & Cho, 2020).

Table 3. Correlations and discriminant validity.

	PU	PEU	ATA	SN	PBC	RT	IAA
PU	1.000	0.363	0.482	0.351	0.48	0.069*	0.427
PEU	0.363	1.000	0.448	0.284	0.421	0.184	0.418
ATA	0.482	0.448	1.000	0.459	0.558	0.107	0.583
SN	0.351	0.284	0.459	1.000	0.451	0.038**	0.506
PBC	0.48	0.421	0.558	0.451	1.000	0.156	0.634
RT	0.069*	0.184	0.107	0.038**	0.156	1.000	0.161
IAA	0.427	0.418	0.583	0.506	0.634	0.161	1.000

Note: ***p < 0.01; **p < 0.05; **p < 0.1. **Source:** own elaboration

Table 4. Reliability and Convergent validity.

Constructs	Items	Convergent validity			Internal consistency reliability		
		Outer loading	AVE	VIF	Cronbach's alpha	Dijkstra-Henseler's (rho_A)	Composite reliability CR
PU	PU1	0.807	0.701	1.766	0.857	0.86	0.903
	PU2	0.809		1.859			
	PU3	0.905		4.132			
	PU4	0.824		3.174			
PEU	PEU1	0.851	0.747	1.842	0.832	0.845	0.898
	PEU2	0.889		1.960			
	PEU3	0.853		1.949			
ATA	ATA1	0.865	0.744	1.937	0.828	0.828	0.897
	ATA2	0.855		1.811			
	ATA3	0.866		1.917			
SN	SN1	0.906	0.804	1.589	0.757	0.761	0.891
	SN2	0.887		1.589			
PBC	PBC1	0.851	0.707	1.640	0.793	0.797	0.879
	PBC2	0.841		1.713			
	PBC3	0.831		1.684			
RT	RT1	0.719	0.612	1.343	0.705	0.892	0.824
	RT2	0.704		1.372			
	RT3	0.908		1.424			
IAA	IAA1	0.854	0.720	1.780	0.806	0.806	0.885
	IAA2	0.834		1.664			
	IAA3	0.857		1.806			

Source: own elaboration

Table 5. HTMT Assessment.

	PU	PEU	ATA	SN	PBC	RT	IAA	RT x PBC	RT x SN	RT x ATT
PU										
PEU	0.426									
ATA	0.570	0.535								
SN	0.433	0.357	0.580							
PBC	0.581	0.516	0.687	0.579						
RT	0.088	0.206	0.144	0.071	0.194					
IAA	0.513	0.509	0.713	0.646	0.790	0.189				
RT x PBC	0.200	0.073	0.277	0.275	0.212	0.341	0.342			
RT x SN	0.223	0.144	0.349	0.292	0.284	0.269	0.393	0.523		
RT x ATT	0.196	0.140	0.247	0.334	0.273	0.252	0.382	0.579	0.508	

Source: own elaboration

Assessing the Structural Model: The inferential statistics were derived using the bootstrapping method with 5,000 subsamples, no sign change, and bias-corrected confidence intervals of 95 percent. Figure 2 and Table 6 display the results of the testing ofatifs. All cognitive determinants, namely perceived usefulness (β= 0.368, p 0.000), perceived ease of use (β = 0.083, p 0.000), attitude toward AI advice (β = 0.231, p 0.000), perceived value (β = 0.235, p 0.01) have a significant effect with attitude toward AI advice. Moreover, attitude toward AI (β = 0.226, p 0.000), social norms (β = 0.171, p 0.000), and perceived behavioral control (β =0.350, p 0.000) exhibited a significant relationship with intention to accept AI advice. Therefore, the examined hypotheses (H1, H2, H3, H4, H5) were validated. Additionally, risk tolerance is respectively reported (β = 0.082, p 0.000; β = 0.084 p 0.000; β = 0.074, p 0.000) to have a significantly moderating effect on the nexus of attitude toward AI, social norms, and perceived behavioral control with an intention to accept AI advice. This issue confirms hypotheses H6, H7 and H8.

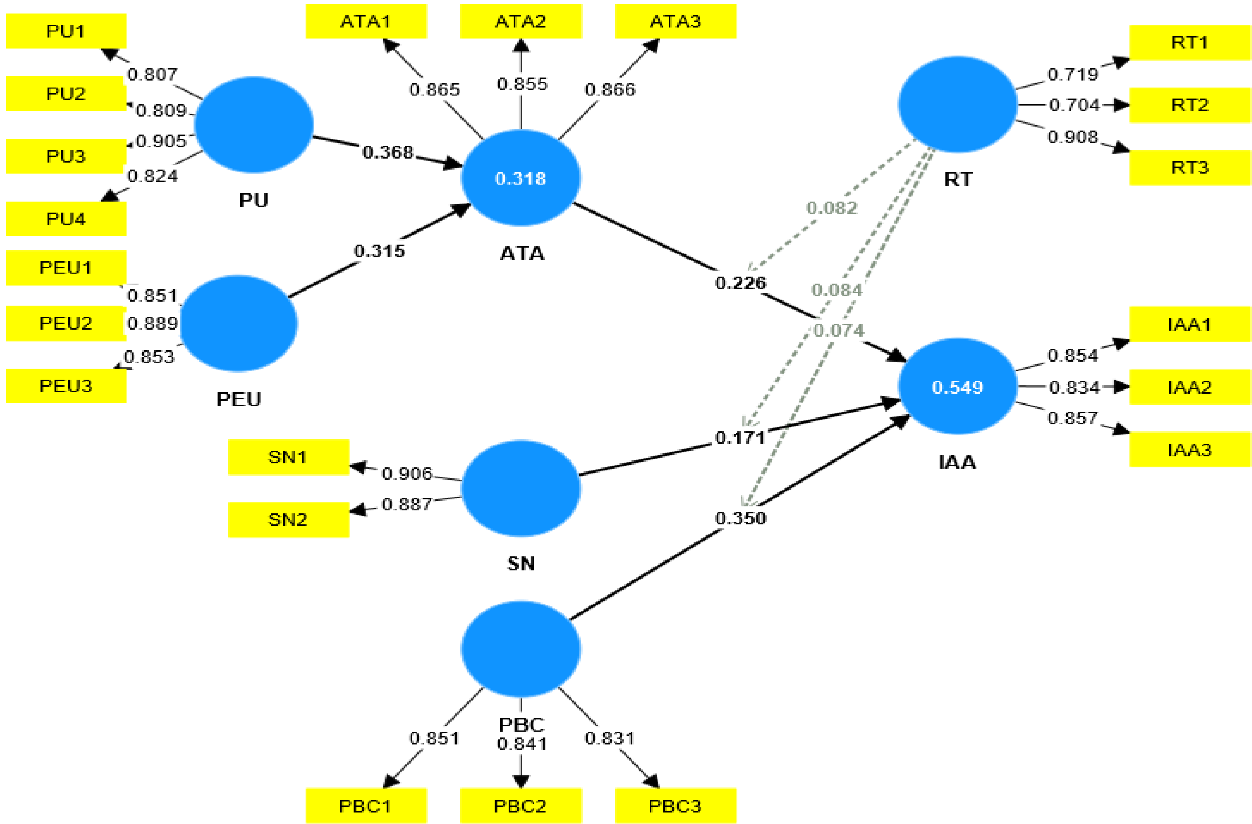

Fig. 2. Structural Model
Source: own elaboration

Table 6. Structural Model.

Hyp.	PLS Path	Path coeff.	STDEV	T-stat	P-value	5.0%	95.0%	Remarks
H1	Perceived usefulness -> Attitude toward AI advice	0.368	0.044	8.394	0.000	0.297	0.440	Significant
H2	Perceived ease of use -> Attitude toward AI advice	0.315	0.040	7.903	0.000	0.249	0.380	Significant
H3	Attitude -> Intention to accept AI advice	0.226	0.040	5.600	0.000	0.164	0.295	Significant
H4	Social norms -> Intention to accept AI advice	0.171	0.037	4.627	0.000	0.112	0.234	Significant
H5	Perceived behavioral control -> Intention to accept AI advice	0.350	0.044	7.933	0.000	0.275	0.421	Significant
H6	The moderating effect of risk tolerance on the link of perceived behavioral control with intention to accept AI advice	0.074	0.044	1.673	0.094	-0.002	0.143	Significant
H7	The moderating effect of risk tolerance on the link of social norms with intention to accept AI advice	0.084	0.037	2.257	0.024	0.023	0.144	Significant
H8	The moderating effect of risk tolerance on the link of attitude toward AI with intention to accept AI advice	0.082	0.040	2.042	0.041	0.016	0.148	Significant

Source: own elaboration

The determination coefficient is a step in the structural model evaluation procedure that employs an R2 value to evaluate the model's predictive ability. ATT (0.316) and IAA (0.543) both had high prediction accuracy (Cohen, 1992). Then, we utilized PLSpredict in SmartPLS 4.0 with 10 folds and 10 repetitions to assess the out-of-sample predictive ability of Q2. For endogenous variables, the range of Q2 for ATT and IAA was consecutively 0.309 and 0.503, which was greater than zero (Hair et al., 2017). Therefore, the model's predictive ability was adequate (Shmueli et al., 2019).

Table 6. Rsquare, Q^2 predict and RMSE.

	R-square	Q^2predict
ATT	0.316	0.309
IAA	0.543	0.503

Source: own elaboration

Discussion

The results confirm that attitude toward AI has a significant positive effect on the intention to accept AI-driven financial advice, consistent with previous studies on technology adoption and AI reliance in financial decision-making (Hoang et al., 2025; Chong et al., 2022). Investors who perceive AI-powered financial tools as useful, reliable, and efficient are more likely to integrate them into their decision-making processes. This reinforces the importance of designing AI-based investment platforms that emphasize usability, transparency, and data-driven accuracy to enhance investor confidence.

Additionally, subjective norms significantly influence AI adoption, highlighting the role of social and professional networks in shaping investor behavior. These findings align with prior research indicating that investors rely on the opinions of financial advisors, institutional endorsements, and peer recommendations when considering new financial technologies (Lourenco et al., 2020). As AI continues to gain acceptance in financial markets, its credibility among professionals and industry leaders will likely drive wider adoption.

Furthermore, perceived behavioral control has a strong positive effect on AI acceptance, suggesting that investors who feel confident in their ability to use AI-based financial tools are more likely to adopt them. This aligns with previous studies emphasizing the role of self-efficacy, financial literacy, and digital experience in AI adoption (Chai et al., 2020; Ashrafi, 2023). Improving AI accessibility, enhancing user education, and ensuring clear interpretability of AI-generated insights can help reduce perceived barriers to adoption and increase investor engagement with AI-powered financial tools.

The results highlight the significant moderating effect of risk tolerance on the relationship between psychological factors and AI adoption, confirming that investors with different risk preferences exhibit distinct behavioral responses to AI-generated financial advice. Specifically, investors with higher risk tolerance are more likely to develop positive attitudes toward AI, trust AI-driven recommendations, and integrate them into their decision-making strategies. These findings align with previous research indicating that risk-seeking investors are more open to AI-powered decision-making due to AI’s ability to eliminate emotional biases and optimize investment strategies (Flavián et al., 2021; Nam & Hwang, 2023).

Conversely, investors with lower risk tolerance demonstrate greater reluctance toward AI adoption, as they prioritize stability, human oversight, and predictability over algorithmic decision-making (Longoni et al., 2019). This suggests that risk-averse investors may require greater transparency, regulatory assurances, and hybrid AI-human advisory models to increase trust in AI-generated recommendations. The study extends prior findings by demonstrating that risk tolerance does not simply affect AI acceptance in isolation but actively moderates the influence of psychological determinants on AI adoption decisions.

Conclusion

Theory contribution

This paper contributes to the literature on human-AI interaction and AI adoption in financial decision-making in several significant ways.

Firstly, it introduces a comprehensive model, building on the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM), that elucidates the intricate relationships between social norms, attitudes toward AI advice, and perceived behavioral control in the context of accepting AI advice in financial decisions. This model advances our understanding of how individuals decide to integrate AI advice into their financial strategies, considering the multifaceted dynamics of trust, perceived accuracy, and risk levels. It provides a nuanced view of user acceptance, demonstrating that the decision to embrace AI is contextually dependent and significantly influenced by the level of risk involved. In situations where risk is perceived as high, individuals exhibit heightened caution and meticulously assess their trust in AI and the perceived accuracy of AI advice before deciding to accept AI-based recommendations.

Secondly, this study pioneers the exploration of risk tolerance as a moderating variable in the acceptance of AI advice in financial decision-making. It adds a novel dimension to the existing literature by scrutinizing how an individual's propensity for risk influences their willingness to adopt AI recommendations. This innovative approach not only deepens the understanding of the interplay between risk tolerance and AI acceptance but also sheds light on the conditions under which individuals are more inclined to rely on AI for making intricate financial decisions that typically demand intuitive judgments. It reveals that even in high-involvement services like finance, where human counsel is traditionally preferred, there exists a potential for AI acceptance, contingent upon attitude, trust, perceived accuracy, and risk level.

Thirdly, the study contributes to the existing body of knowledge by delving into the uncharted territory of intention to accept AI advice within the complex landscape of the financial industry. It represents one of the earliest attempts to systematically investigate the myriad elements influencing individuals' inclination to incorporate AI-generated advice into their financial decision-making processes. By meticulously examining the multifaceted dynamics underpinning human-AI interaction in the financial sector, this study provides valuable insights and enhances our comprehension of the evolving landscape of human-AI collaboration in contexts that are inherently intimate and complex.

Practical implication

This research delineates pivotal practical implications for investors through the integration of AI advice, underscoring its transformative potential in investment decision-making processes. The assimilation of AI advice serves as a linchpin for refined and informed investment strategies, enabling investors to leverage advanced analytical and predictive capabilities, thereby optimizing investment selections and risk assessments. AI advice provides investors with nuanced insights into financial markets, offering real-time analyses and trend predictions which are crucial for navigating the intricate landscapes of investment environments. This integration facilitates the formulation of personalized investment recommendations, meticulously tailored to individual risk tolerances, preferences, and financial objectives, allowing for the construction of diversified and resilient portfolios.

Moreover, the utilization of AI advice enhances efficiency, automating analytical tasks and enabling a focus on strategic portfolio management and decision-making. For investors contending with the volatility of financial markets, AI advice is instrumental in mitigating risks and maximizing returns, fostering financial sustainability and providing a competitive advantage. In summary, the practical incorporation of AI advice represents a significant innovation in investment strategies, with the potential to profoundly impact investor behavior, decision-making mechanisms, and financial outcomes, paving the way for a new paradigm in investment management.

Limitation and future research

Firstly, the research may be constrained by the potential lack of diversity in the sample population, which could limit the generalizability of the findings to broader and more diverse populations. A more heterogeneous sample encompassing varied demographic, socio-economic, and professional backgrounds would offer richer and more nuanced insights into the multifaceted dynamics of AI advice adoption among investors.

Secondly, the study primarily focuses on the integration of AI advice in the financial sector, potentially overlooking the varied applications and implications of AI advice in other high-stakes and high-involvement sectors such as healthcare and legal services. The specificity of the financial context may limit the applicability of the findings to other domains, where the dynamics of trust, risk tolerance, and decision-making may manifest differently.

References

Ashoori, M., & Weisz, J. D. (2019). In ai we trust? factors that influence trustworthiness of AI-infused decision-making processes. *DeepAI.* https://deepai.org/publication/in-ai-we-trust-factors-that-influence-trustworthiness-of-ai-infused-decision-making-processes

Ashrafi, D. M. (2023). *Managing Consumers' Adoption of Artificial Intelligence-Based Financial Robo-Advisory Services: A Moderated Mediation Model. Journal of Indonesian Economy and Business*. Faculty of Economics and Business, Universitas Gadjah Mada. https://doi.org/10.22146/jieb.v38i3.6242

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, 50, 179-211. http://dx.doi.org/10.1016/0749-5978(91)90020-T

Addy, W., Nifise, A. A., Bello, B., Tula, S. T., & Odeyemi, O. (2024). (PDF) Transforming Financial Planning with AI-Driven Analysis: A review and Application Insights. *International Journal of Science and Research Archive*. https:// doi: 10.30574/wjaets.2024.11.1.0053

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In ai we trust? perceptions about automated decision-making by Artificial Intelligence. *Society*, *35*(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In Action control (pp. 11-39). *Berlin, Heidelberg: Springer*. https://doi.org/10.1007/978-3-642-69746-3_2

Ben-David, I., & Hirshleifer, D. A. (2011). Are investors really reluctant to realize their losses? trading responses to past returns and the disposition effect. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1876594

Bao, T., Gao, J., Wang, J., Chen, Y., Xu, F., Qiao, G., & Li, F. (2023). A global bibliometric and visualized analysis of gait analysis and Artificial Intelligence Research from 1992 to 2022. *Frontiers in Robotics and AI*, *10*. https://doi.org/10.3389/frobt.2023.1265543

Bao, L., Krause, N. M., Calice, M. N., Scheufele, D. A., Wirz, C. D., Brossard, D., Newman, T. P., & Xenos, M. A. (2022). Whose ai? how different publics think about AI and its social impacts. *Computers in Human Behavior*, *130*, 107182. https://doi.org/10.1016/j.chb.2022.107182

Bajdor, P., Pawełoszek, I., & Fidlerova, H. (2021). Analysis and assessment of sustainable entrepreneurship practices in Polish small and medium enterprises. *Sustainability*, *13*(7), 3595. https://doi.org/10.3390/su13073595

Binh, N. T. H., Dang, T.-Q., & Nguyen, L.-T. (2024). Metaverse: The Future for Immersive Logistics and International Business Education. *Journal of Teaching in International Business*, *35*(3–4), 75–107. https://doi.org/10.1080/08975930.2024.2445861

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2019). Personalized robo-advising: Enhancing investment through client interactions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3453975

Chai, C. S., Wang, X., & Xu, C. (2020). An Extended Theory of Planned Behavior for the Modelling of Chinese Secondary School Students' Intention to Learn Artificial Intelligence. *Mathematics*. https://doi.org/10.3390/math8112089

Cheng, M., Li, X., & Xu, J. (2022). Promoting Healthcare Workers' adoption intention of artificial-intelligence-assisted diagnosis and treatment: The chain mediation of social influence and Human–Computer Trust. *International Journal of Environmental Research and Public Health*, *19*(20), 13311. https://doi.org/10.3390/ijerph192013311

Chong, A. Y. L., Ooi, K. B., Lin, B., & Bao, H. (2012), An empirical analysis of the determinants of 3G adoption in China. *Computers in Human Behavior*, 28(2), 360-369. https://doi.org/10.1016/j.chb.2011.10.005

Cohen, J. (1992). A power primer, *Psychological Bulletin*, *112*(1), 155-159.

Diakopoulos, N., & Koliska, M. (2016). Algorithmic transparency in the news media. *Digital Journalism*, *5*(7), 809–828. https://doi.org/10.1080/21670811.2016.1208053

Davis, F. (1989) Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13, 319-340. https://doi.org/10.2307/249008

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2014). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2466040

Flavián, C., Ibáñez-Sánchez, S., & Orús, C. (2021). Integrating virtual reality devices into the body: Effects of technological embodiment on customer engagement and behavioral intentions toward the destination. *Future of Tourism Marketing*, 79–94. https://doi.org/10.4324/9781003176039-8

Fortune Business Insights. Artificial Intelligence [AI] Market Size, Growth & Trends, 2032. (2022). Available at: https://www.fortunebusinessinsights.com/industry-reports/artificial-intelligence-market-100114

Gaudiello, I., Zibetti, E., Lefort, S., Chetouani, M., & Ivaldi, S. (2016). Trust as indicator of robot functional and social acceptance. an experimental study on user conformation to icub answers. *Computers in Human Behavior*, *61*, 633–655. https://doi.org/10.1016/j.chb.2016.03.057

Gupta, S., & Singh, A. (2024). Investor's satisfaction in Artificial Intelligence-supported share trading apps: Mediation and Parallel Moderation Analysis. *International Studies of Management & Organization*, 1–25. https://doi.org/10.1080/00208825.2024.2442191

Horowitz, M. C., Kahn, L., Macdonald, J., & Schneider, J. (2023). Adopting ai: How familiarity breeds both trust and contempt. *AI & Society*, *39*(4), 1721–1735. https://doi.org/10.1007/s00146-023-01666-5

Ho, C.-M. (2023). Research on interaction of innovation spillovers in the AI, Fin-Tech, and IOT Industries: Considering structural changes accelerated by COVID-19. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-022-00403-z

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems*, 117(3), 442-458. https://doi.org/10.1108/IMDS-04-2016-0130

Huynh, M.-T. (2024). Using generative AI as decision-support tools: Unraveling users' trust and ai appreciation. *Journal of Decision Systems*, 1–32. https://doi.org/10.1080/12460125.2024.2428166

Hoang, S. D., Dey, S. K., Pham, T. P., & Tučková, Z. (2023). Harnessing the power of virtual reality: Enhancing telepresence and inspiring sustainable travel intentions in the tourism industry. *Technology in Society*, 102378. https://doi.org/10.1016/j.techsoc.2023.102378

Hoang, S. D., Nguyen, T. H.-H., Dey, S. K., & Thi Thu, H. D. (2025). Beyond the hype: AI advice and investor dissonance in crypto trading. *Current Psychology*. https://doi.org/10.1007/s12144-025-07430-w

Hoogland, J. J., & Boomsma, A. (1998). Robustness Studies in Covariance Structure Modeling: An Overview and a Meta-Analysis. Sociological Methods & Research, 26, 329-367.https://doi.org/10.1177/0049124198026003003

Jiao, J., & Cao, X. (2024). Research on designers' behavioral intention toward Artificial Intelligence-aided design: Integrating the theory of planned behavior and the Technology Acceptance Model. *Frontiers in Psychology*, *15*. https://doi.org/10.3389/fpsyg.2024.1450717

Jacobsen, R. M., Bysted, L. B., Johansen, P. S., Papachristos, E., & Skov, M. B. (2020). Perceived and measured task effectiveness in human-AI collaboration. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–9. https://doi.org/10.1145/3334480.3383104

Kumar, Y., Koul, A., Singla, R., & Ijaz, M. F. (2022). Artificial Intelligence in disease diagnosis: A systematic literature review, synthesizing framework and future research agenda. *Journal of Ambient Intelligence and Humanized Computing*, *14*(7), 8459–8486. https://doi.org/10.1007/s12652-021-03612-z

Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7), 546–580. https://doi.org/10.17705/1jais.00302

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, 101925. https://doi.org/10.1016/j.tele.2022.101925

Leong, L.-Y., Hew, T.-S., Ooi, K.-B., & Chau, P. Y. K. (2024). "to share or not to share?" – a hybrid Sem-Ann-NCA study of the enablers and enhancers for mobile sharing economy. *Decision Support Systems*, *180*, 114185. https://doi.org/10.1016/j.dss.2024.114185

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Liang, W., Tadesse, G. A., Ho, D., Fei-Fei, L., Zaharia, M., Zhang, C., & Zou, J. (2022a). Advances, challenges and opportunities in creating data for trustworthy AI. *Nature Machine Intelligence*, *4*(8), 669–677. https://doi.org/10.1038/s42256-022-00516-1

Liao, J., Liu, T., Tang, X., Mu, X., Huang, B., & Cao, D. (2020). Decision-making strategy on highway for autonomous vehicles using Deep Reinforcement Learning. *IEEE Access*, *8*, 177804–177814. https://doi.org/10.1109/access.2020.3022755

Lee, J. A., Hilty, R., & Liu, K. C. (2021). *Artificial Intelligence and intellectual property*. Oxford: Google Books.

Longoni, C, Bonezzi, A., & Morewedge, C.K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research*, 629–650, https://doi.org/10.1093/jcr/ucz013

Loewenstein, G. F., O'Donoghue, T., & Rabin, M. (2000). Projection bias in predicting future utility. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.239901

Lourenco, C. J., Dellaert, B. G. C., & Donkers, B. (2020). Whose Algorithm Says So: The Relationships Between Type of Firm, Perceptions of Trust and Expertise, and the Acceptance of Financial Robo-Advice. *Journal of Interactive Marketing*. https://doi.org/10.1016/j.intmar.2019.10.003

Libório, M. P., Diniz, A. M., Vieira, D. A., & Ekel, P. I. (2024). Subjective–objective method of maximizing the average variance extracted from sub-indicators in composite indicators. *Social Indicators Research*, *175*(2), 613–637. https://doi.org/10.1007/s11205-024-03385-w

Miziołek, T. (2021). Employing Artificial Intelligence in investment management. *The Digitalization of Financial Markets*, 161–174. https://doi.org/10.4324/9781003095354-9

Madanchian, M. (2024). The impact of artificial intelligence marketing on e-commerce sales. *Systems*, *12*(10), 429. https://doi.org/10.3390/systems12100429

Northey, G., Hunter, V., Mulcahy, R., Choong, K., & Mehmet, M. (2022). Man vs machine: How artificial intelligence in banking influences consumer belief in financial advice. *International Journal of Bank Marketing*, *40*(6), 1182–1199. https://doi.org/10.1108/ijbm-09-2021-0439

Nam, J. G., Hwang, E. J., Kim, J., Park, N., Lee, E. H., Kim, H. J., Nam, M., Lee, J. H., Park, C. M., & Goo, J. M. (2023). AI improves nodule detection on chest radiographs in a health screening population: A randomized controlled trial. *Radiology*, *307*(2). https://doi.org/10.1148/radiol.221894

Nguyen, L., Gallery, G., & Newton, C. J. (2016). (PDF) the influence of financial risk tolerance on investment decision-making in a financial advice context. *Australasian Accounting Business and Finance Journal*. Https://doi.org/10.14453/aabfj.v10i3.2

Ochmann, J., Michels, L., Tiefenbeck, V., Maier, C., & Laumer, S. (2024). Perceived algorithmic fairness: An empirical study of transparency and anthropomorphism in algorithmic recruiting. *Information Systems Journal*, *34*(2), 384–414. https://doi.org/10.1111/isj.12482

Ooi, K. B., Foo, F. E., Tan, G. W. H., Hew, J. J., & Leong, L. Y. (2020). Taxi within a grab? A gender-invariant model of mobile taxi adoption. *Industrial Management & Data Systems*, 57(3), 102–120. https://doi.org/10.1108/IMDS-04-2020-0239

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *52*(3), 381–410. https://doi.org/10.1177/0018720810376055

Phan, L.-G. N., Tri, D. Q., Dang, S.-H., & Nguyen, L.-T. (2025). Hooked on Livestreaming: What Drives Customer Repurchase Intention in E-Commerce? *Journal of Creative Communications*. https://doi.org/10.1177/09732586241311001

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A Social Relationship Perspective to designing information systems. *Journal of Management Information Systems*, *25*(4), 145–182. https://doi.org/10.2753/mis0742-1222250405

Riedel, A., Mulcahy, R., & Northey, G. (2022). Feeling the love? how consumer's political ideology shapes responses to AI Financial Service delivery. *International Journal of Bank Marketing*, *40*(6), 1102–1132. https://doi.org/10.1108/ijbm-09-2021-0438

Rimal, R. N. (2003). Understanding the influence of perceived norms on behaviors. *Communication Theory*, *13*(>2), 184–203. https://doi.org/10.1093/ct/13.2.184

Rzepka, C., & Berger, B. (2018). User interaction with AI-enabled systems: A systematic review of is research. *AIS Electronic Library (AISeL) - ICIS 2018 Proceedings: User Interaction with AI-enabled Systems: A Systematic Review of IS Research.* https://aisel.aisnet.org/icis2018/general/Presentations/7/

Rönkkö, M., & Cho, E. (2020). An updated guideline for assessing discriminant validity. *Organizational Research Methods*, *25*(1), 6–14. https://doi.org/10.1177/1094428120968614

Shou, Y., & Olney, J. (2022). Measuring Risk Tolerance across Domains: Scale Development and Validation. *Journal of Personality Assessment*, *104*(4), 484–495. https://doi.org/10.1080/00223891.2021.1966019

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using plspredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/ejm-02-2019-0189

Soper, D.S. (2023). A-priori Sample Size Calculator for Structural Equation Models [Software]. Available from https://www.danielsoper.com/statcalc

Sadriwala, M. F., & Sadriwala, K. F. (2022). Perceived usefulness and ease of use of artificial intelligence on Marketing Innovation. *International Journal of Innovation in the Digital Economy*, *13*(1), 1–10. https://doi.org/10.4018/ijide.292010

Sukandar, F., & Hermawan, S. (2022). Fintech adoption for SME development: Perceived usefulness and ease of use. *Academia Open*, *7*. https://doi.org/10.21070/acopen.7.2022.3469

Schaffer, J., O'Donovan, J., Michaelis, J., Raglin, A., & Höllerer, T. (2019). I can do better than your AI. *Proceedings of the 24th International Conference on Intelligent User Interfaces*, 240–251. https://doi.org/10.1145/3301275.3302308

Singh Channe, P. (2024). (PDF) the impact of AI on economic forecasting and policy-making: Opportunities and challenges for future economic stability and growth. *AI in Economic Forecasting and Policy*. Available at: Makinghttps://www.researchgate.net/publication/382827405_The_Impact_of_AI_on_Economic_Forecasting_and_Policy-Making_Opportunities_and_Challenges_for_Future_Economic_Stability_and_Growth

Tomsett, R., Preece, A., Braines, D., Cerutti, F., Chakraborty, S., Srivastava, M., Pearson, G., & Kaplan, L. (2020). Rapid trust calibration through interpretable and uncertainty-aware AI. *Patterns*, *1*(4), 100049. https://doi.org/10.1016/j.patter.2020.100049

Teo, A. C., Tan, G. W. H., Ooi, K. B., & Lin, B. (2015). Why consumers adopt mobile payment? A partial least squares structural equation modelling (PLS-SEM) approach. International Journal of Mobile Communications, 13(5), 478-497. https://doi.org/10.1504/IJMC.2015.070961

Yu, L., & Li, Y. (2022). Artificial Intelligence decision-making transparency and employees' trust: The parallel multiple mediating effect of effectiveness and discomfort. *Behavioral Sciences*, *12*(5), 127. https://doi.org/10.3390/bs12050127

Venkatesh, Morris, Davis, & Davis. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, Thong, & Xu. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of Technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Westland, C. J. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications*, *9*(6), 476–487. https://doi.org/10.1016/j.elerap.2010.07.003

Wickramasinghe, C. S., Marino, D. L., Grandio, J., & Manic, M. (2020). Trustworthy AI development guidelines for human system interaction. *2020 13th International Conference on Human System Interaction (HSI)*, 130–136. https://doi.org/10.1109/hsi49210.2020.9142644

Yao, M. (2024). (PDF) how is AI enhancing investment behavior in today's financial markets. *International Journal of Emerging Multidiciplinaries Social Science*. https://doi.org/10.54938/ijemdss.2024.03.1.359

Yang, Q., & Lee, Y.-C. (2024). Enhancing financial advisory services with genai: Consumer perceptions and attitudes through service-dominant logic and artificial intelligence device use acceptance perspectives. *Journal of Risk and Financial Management*, *17*(10), 470. https://doi.org/10.3390/jrfm17100470

Zhu, H., Vigren, O., & Söderberg, I.-L. (2024). Implementing Artificial Intelligence Empowered Financial Advisory Services: A literature review and critical research agenda. *Journal of Business Research*, *174*, 114494. https://doi.org/10.1016/j.jbusres.2023.114494

Złotowski, J., Yogeeswaran, K., & Bartneck, C. (2017). Can we control it? autonomous robots threaten human identity, uniqueness, safety, and resources. *International Journal of Human-Computer Studies*, *100*, 48–54. https://doi.org/10.1016/j.ijhcs.2016.12.008