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# AI for Financial Advice, Fraud Loss, and the Moderating Effect of Financial Knowledge Miscalibration

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## Abstract

There is growing interest in using AI for financial advice, yet fraud and related financial losses remain widespread. While previous research has examined fraud victimization in general, there has been less focus on the losses resulting from fraud. Additionally, there is a limited understanding of whether individuals' willingness to use AI for financial advice is linked to these losses. This study utilizes data from the 2024 National Financial Capability Study (NFCS) and is grounded in Routine Activity Theory and Bounded Rationality. It examines the relationship between the willingness to use AI for financial advice and the likelihood of experiencing loss due to fraud. Furthermore, the study examines the moderating effect of financial knowledge miscalibration (overconfidence). Results from multivariate logistic regression models indicate a statistically significant interaction between the willingness to use AI and financial knowledge miscalibration. Specifically, overconfidence was positively associated with the likelihood of experiencing loss due to fraud among individuals who were willing to use AI for financial advice, whereas this association was not observed among those who were not willing to use AI. These findings have important implications for financial professionals and stakeholders involved in preventing fraud.

**Keywords:** AI for financial advice; fraud victimization; fraud loss; financial knowledge miscalibration (overconfidence)

## 1. Introduction

Fraud refers to an activity that uses deception to obtain gain and becomes a crime when it involves the knowing misrepresentation of the truth or concealment of a material fact to induce another person to act to their detriment ([Association of Certified Fraud Examiners, n.d.](#)). Within this broader framework, individual financial fraud has been defined as intentionally and knowingly deceiving the victim by misrepresenting, concealing, or omitting facts about promised goods, services, or other benefits and consequences that are nonexistent, unnecessary, never intended to be provided, or deliberately distorted for the purpose of monetary gain ([Beals et al., 2015](#); [Golladay & Snyder, 2023](#)). Fraud losses can stem from a range of tactics, including imposter scams, investment scams, and email scams ([Federal Trade Commission, 2025](#)). Federal Trade Commission (FTC) sources further suggest that scammers are using emerging digital technologies, including tools such as voice cloning, to make fraud schemes more sophisticated ([Federal Trade Commission, 2024](#)).



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Financial fraud continues to be a far-reaching and devastating problem, with annual losses in the billions of dollars (FINRA Investor Education Foundation & AARP Fraud Watch Network, 2022). Individual financial fraud has led to a sizable increase in monetary losses, despite no significant increase in the number of reported fraud cases (Federal Trade Commission, 2025). According to the Federal Trade Commission (2024), consumers in the United States (US) reported losing over \$12.5 billion to fraud in 2024, representing a 25% increase over the prior year. By 2028, global losses to online payment fraud alone are projected to reach \$362 billion (Mastercard, 2025).

Beyond the monetary losses, the emotional repercussions are significant (FINRA Investor Education Foundation & AARP Fraud Watch Network, 2022). Sixty-nine percent of victims report mental health impacts after experiencing fraud. Some victims experience emotional distress, including depression, anxiety, shame, and embarrassment, which can manifest in lasting negative effects on mental well-being (Lloyds Banking Group, 2024).

As financial fraud grows in scale and complexity, many consumers are simultaneously navigating greater financial stress and seeking new sources of guidance. A growing number of consumers are seeking financial advice as their financial stress increases (Britt et al., 2015; CFP Board, 2015). At the same time, advances in artificial intelligence (AI) are transforming how individuals access financial information and advice (Belanche et al., 2019; Jung et al., 2018). AI-enabled tools are increasingly used to support budgeting, investing, and financial planning. Recent survey data indicate that 51% of respondents rely on AI for financial information or guidance, while an additional 27% are considering it (Williams, 2025).

These technologies offer advantages such as accessibility, scalability, and lower costs relative to traditional human advice, but they also introduce new risks and uncertainties (Belanche et al., 2019; D'Acunto et al., 2019; Jung et al., 2018). Individuals who are willing to rely on AI for financial advice may differ from those who prefer traditional sources in ways that influence vulnerability to fraud, including differences in trust, financial knowledge, and confidence. Although AI can enhance fraud detection through machine learning, natural language processing, and predictive analytics (Ngai et al., 2011; Sun et al., 2025), the same technology has also created new opportunities for online fraudsters. Prior research shows that willingness to adopt AI-enabled financial advice is influenced by behavioral factors, including perceived credibility, trust, and financial knowledge, with overconfidence associated with a greater propensity to accept algorithmic advice (Belanche et al., 2019; Chang et al., 2026; Zhu et al., 2024). Importantly, overconfidence and lower objective financial knowledge have also been linked to increased susceptibility to financial fraud (Cucinelli & Soana, 2023; Isaia et al., 2024). Despite the expansion of AI-enabled financial advice, limited research has examined whether willingness to use AI for financial advice is associated with fraud-related financial loss.

This study addresses this gap by examining the relationship between willingness to use AI for financial advice and the likelihood of experiencing fraud-related financial loss. Drawing on Routine Activity Theory and Bounded Rationality, this study conceptualizes willingness to use AI as a behavioral characteristic that may influence both individuals' exposure to fraud risk and their capacity to recognize and respond to fraudulent schemes. Routine Activity Theory suggests that individuals' routine behaviors and interactions with financial systems may affect their visibility and accessibility to motivated offenders, while Bounded Rationality emphasizes the cognitive constraints that limit individuals' ability to evaluate complex financial information and identify deception. Using data from the 2024 National Financial Capability Study (NFCS), a nationally representative sample of U.S. adults, this study examines whether willingness to use AI for financial advice is associated with fraud-related financial loss and whether this relationship is moderated by financial knowledge and miscalibrations of subjective and objective knowledge. These findings align

with the Association of Certified Fraud Examiners (ACFE) position that regulators could impose additional requirements related to fraud detection and prevention on financial institutions (Wilder, 2025).

The findings provide evidence that willingness to use AI for financial advice is significantly associated with fraud-related financial loss, and that this relationship varies based on individuals' financial knowledge and financial knowledge calibration. Specifically, overconfidence, defined as higher self-assessed financial knowledge relative to objective financial knowledge, strengthens the association between willingness to use AI and the likelihood of experiencing financial loss due to fraud. In contrast, higher levels of objective financial knowledge are associated with lower odds of fraud-related loss. Together, these findings suggest that behavioral and cognitive factors play a meaningful role in shaping vulnerability to fraud in an increasingly digital financial environment. These findings are consistent with the ACFE and the Committee of Sponsoring Organizations of the Treadway Commission's (COSO) recommendation for a risk-based approach to fraud management that allocates resources based on the likelihood of loss due to fraud among certain vulnerable populations (COSO & ACFE, 2023).

This study makes three key contributions to the literature. First, it extends research on financial fraud by shifting the focus from occurrences or frequency of victimization to fraud-related financial loss, an outcome that more directly captures harm to consumers. Second, it introduces willingness to use AI for financial advice as a behavioral characteristic associated with fraud outcomes, bridging previously disconnected literature on fintech adoption and fraud vulnerability. Third, this study advances theory by demonstrating that financial knowledge miscalibration (overconfidence) conditions the relationship between willingness to adopt AI and fraud loss, highlighting the importance of cognitive biases in shaping financial risk in increasingly digital environments.

This paper proceeds as follows. Section 2 reviews the relevant literature on AI-enabled financial advice, financial fraud, and financial knowledge, and presents the study hypotheses. Section 3 describes the theoretical framework, data, measures, and analytical methods. Section 4 presents empirical results. Section 5 discusses the findings and their implications. Section 6 offers a conclusion and directions for future research.

## 2. Literature Review

Recent advances in AI technology have transformed how consumers access financial information, complete financial transactions, and receive financial advice. At the same time, these changes have altered the landscape of financial fraud, creating new opportunities for exploitation. Understanding consumer vulnerability in an increasingly digital financial environment requires integrating insights from multiple strands of research. Although scholars have examined AI-enabled financial advice, fraud detection, and financial fraud victimization separately, relatively little work has examined how these domains intersect. This review will synthesize these areas of research to support testable hypotheses for the relationship between the willingness to adopt AI for financial advice and vulnerability to financial fraud.

### 2.1. Artificial Intelligence (AI)–Financial Information and Advice

The increasing popularity of algorithm-driven financial advisory services, such as robo-advisors, is indicative of the growing role of AI in the financial information and advice space. Positioning AI as a visible intermediary in consumers' financial decisions and outcomes underscores the importance of understanding how consumers engage with this medium. Interestingly, research has found that anthropomorphic, or human-like, traits in AI advice improve acceptance of that source at levels similar to those of romantic

partners (Hermann & Alberhasky, 2025). Piehlmaier (2022) also identified overconfidence as a behavioral trait found in investors with a higher propensity to accept algorithmic financial advice. While many empirical studies consider the intent to adopt advice and recommendations provided by algorithmic platforms such as robo-advisors when examining its use, Zhu et al. (2023) noted that actual adoption requires some baseline level of financial knowledge before the recommendation can be understood and acted upon. They cite several factors to support this conclusion, including the absence of human experts framing and explanation of the information received, as well as the need to interpret the written or visually presented information received. Without this support, individuals need to rely on their own knowledge and understanding. Although prior studies suggest that financial knowledge may improve an individual's ability to evaluate and adopt AI-enabled financial advice, less is known about whether it also reduces vulnerability to financial fraud or related losses. This unresolved question motivates the present study.

## 2.2. Artificial Intelligence (AI)–Fraud Detection

The use of AI in fraud detection has also drawn the attention of scholars, particularly in the financial services domain. A wide range of financial fraud schemes, ranging from identity theft to phishing scams, can be identified with AI techniques. For example, natural language processing, machine learning algorithms, and even predictive analytics can provide solutions for detecting and preventing financial fraud (Bello & Olufemi, 2024; Faulhaber & Chaffin, 2024). Sun et al. (2025) found that advancements in AI technology significantly reduce both the likelihood and the severity of financial fraud, as AI-driven processes make irregular activity easier to detect and harder to conceal. The use of AI in this capacity has also highlighted its value in the regulatory technology (RegTech) domain by improving oversight and enhancing fraud detection (Bagherifam et al., 2025). While prior research highlights institutional applications, and the technology appears promising for fraud detection, limited attention has been given to whether individuals trust, adopt and effectively use these tools.

## 2.3. Financial Fraud

Financial fraud has been defined as deliberate deception for monetary gain, through means such as misrepresentation or omission of important facts about promised goods or services (Beals et al., 2015; Golladay & Snyder, 2023). In their examination of the consequences of financial fraud specifically, Golladay and Snyder (2023) highlighted the victim's willingness to participate in the fraud as an important characteristic of this type of financially motivated crime. Other scholars note that victims are often drawn to these types of financial schemes by people they are familiar with, i.e., friends and family, and the more their financial information is available to the perpetrators, the more likely they are to become a target of financial fraud (Bar Lev et al., 2022; Fan & Yu, 2022).

Low levels of objective financial knowledge and overconfidence have been found to be associated with vulnerability to financial fraud (Bar Lev et al., 2022; Cucinelli & Soana, 2023; Engels et al., 2021; Kadoya et al., 2021; Zhu et al., 2023). Specifically, Cucinelli and Soana (2023) noted that those who are financially confident but wrong, i.e., overconfident, are more likely to fall victim to financial fraud, while those who admit what they do not know because they lack confidence are less likely to be defrauded. Xiao et al. (2022), using the China Family Panel Studies (CFPS), also investigated whether people who are overconfident in their financial knowledge are more likely to be victims of investment fraud. They found that wealthy, male, and educated respondents were overconfident in financial knowledge. However, after controlling for objective financial knowledge, subjective financial knowledge was positively related to the risk of investment fraud victimization. Interestingly, good money

management behaviors are not a substitute for high levels of financial knowledge when it comes to detecting financial fraud (Engels et al., 2021).

In a review of the literature, Bar Lev et al. (2022) reported that scholars consistently found that most victims of financial fraud were male and employed but identified no clear trends in the level of education or marital status of victims. Over the last decade, many studies have identified older adults as most likely to become victims of financial fraud (Bar Lev et al., 2022; Burnes et al., 2017). However, evidence suggests that demographic characteristics alone may be less informative than financial profile and exposure. For example, DeLiema et al. (2020) found no significant relationship between age, gender, or education and financial fraud among older Americans, but showed that types of wealth can influence exposure to specific fraud risks, with individuals holding greater non-housing wealth more likely to be exposed to investment fraud. Despite growing evidence of who might be vulnerable to this type of malfeasance, we do not yet understand how AI may play a role in exposing or protecting individuals from financial fraud. This study helps fill this gap by examining the relationship between an individual's receptiveness to using AI for financial advice and the likelihood that they become victims of financial fraud. Objective and subjective financial knowledge will also be examined to understand its role in moderating this relationship.

#### 2.4. Theory

The theoretical framework for this study integrates two perspectives that are useful for an exploration of financial fraud victimization. The primary lens is Routine Activity Theory, which posits that criminal events occur in an environment where three essential elements converge in time and space: (1) a motivated offender, (2) a suitable target, and (3) the absence of capable guardianship (Cohen & Felson, 1979; Miró, 2014). The offender is anyone with a motive and the capacity to commit a crime (Miró, 2014). The suitable target or victim is defined by four attributes that influence their vulnerability: value, inertia, visibility, and access (Cohen & Felson, 1979; Miró, 2014). To put it in a financial context, suitable targets include individuals with accessible assets and whose patterns of human or daily activities make them readily apparent to motivated offenders or potential fraudsters. Capable guardianship represents the presence of individuals or authorities whose surveillance, whether actual or symbolic, deters potential criminal events and protects potential targets (Hollis-Peel et al., 2011; Miró, 2014). Guardians may include family members who monitor accounts, financial advisors who review transactions, or institutional safeguards such as fraud detection systems.

Routine activities are defined by a person's daily recurring and prevalent activities which provide for their basic needs (Hollis-Peel et al., 2011). When the essential elements converge in time and space, the theory suggests that an individual's routine activities contribute to their risk of victimization (Hollis-Peel et al., 2011; Podaná, 2017). Importantly, victimization risk stems not from inherently risky behaviors, but from the routine performance of legitimate activities that create opportunities for crime (Miró, 2014). For instance, many legitimate technological advances, which increase time spent online, may be exploited by offenders for illegitimate purposes, demonstrating how ordinary activities away from traditional protected spaces can elevate exposure to motivated offenders in the absence of capable guardianship (Miró, 2014; Pratt & Turanovic, 2016). According to Suzuki et al. (2025), certain sociodemographic factors, such as marital status, gender, and income, as well as individual traits like risk-seeking and temper and routine online activities, may increase the convergence of motivated offenders and suitable targets in the absence of capable guardianship.

The secondary theoretical lens is Bounded Rationality, which recognizes that decision makers operate with cognitive limitations that constrain their ability to optimize choices in complex financial environments (Simon, 2000). The Bounded Rationality theory posits that human rationality is constrained by the knowledge that decision makers possess, their ability to access and utilize that knowledge when relevant, their capacity to evaluate consequences of actions, and their capability to manage uncertainty (Simon, 2000). Bounded Rationality recognizes that decision makers prefer satisficing (“good enough”) rather than maximizing and will search for alternatives until one is found that meets an aspiration level rather than continuing to search for the optimal solution (Simon, 1955, 1956). This reflects practicality in that the costs of acquiring information often exceed the benefits of maximizing solutions. As it relates to making financial decisions, Bounded Rationality occurs when uncertainty about future outcomes encounters complex financial products that exceed individuals’ ability to fully evaluate alternatives, when individuals operate with incomplete knowledge of the financial marketplace which includes a limited awareness of risks such as fraud, and when individuals experience cognitive limitations that constrain their ability to recognize potential threats and respond appropriately (Simon, 2000). The framework is particularly relevant to understanding vulnerability to financial fraud because motivated offenders take advantage of their targets’ cognitive limitations by designing schemes that overwhelm information processing capabilities, create time pressure preventing careful thought, and exploit financial knowledge gaps.

Integrating Routine Activity Theory and Bounded Rationality provides a comprehensive framework for studying financial fraud victimization. Routine Activity Theory identifies the structural conditions under which victimization occurs, while Bounded Rationality explains why individuals fail to recognize or respond effectively to fraud risk due to cognitive constraints and satisficing behavior (Simon, 1955, 2000). Together, these perspectives suggest that willingness to use AI for financial advice shapes both individuals’ exposure to fraud risk and their cognitive capacity to respond to it, motivating the following hypotheses.

**H1.** *Willingness to use AI for financial advice is associated with the likelihood of financial loss from fraud.*

Willingness to use AI for financial advice may relate to fraud loss through two competing pathways. First, engagement with AI-enabled financial tools may increase time spent in digital financial environments, elevating visibility and accessibility to motivated offenders, including exposure to AI-facilitated schemes (Federal Trade Commission, 2024; Sun et al., 2025). Second, willingness to use AI may reflect broader digital familiarity that reduces susceptibility to fraud (Li et al., 2024). Because these pathways operate in opposing directions, the net relationship is an empirical question.

**H2.** *Objective financial knowledge significantly moderates the relationship between willingness to use AI for financial advice and the likelihood of experiencing financial loss due to fraud.*

Under Bounded Rationality, objective financial knowledge equips individuals with a more accurate mental model of financial systems, enabling them to evaluate offers and detect deceptive schemes (Simon, 2000). From a Routine Activity Theory perspective, this knowledge functions as cognitive guardianship, an internal capacity that reduces suitability as a fraud target (Hollis-Peel et al., 2011). Higher objective knowledge may amplify the protective effect of AI engagement, while lower knowledge may undermine it, leaving individuals unable to identify fraudulent information in digital environments (Zhu et al., 2023).

**H3.** *Subjective financial knowledge significantly moderates the relationship between willingness to use AI for financial advice and the likelihood of experiencing financial loss due to fraud.*

Subjective financial knowledge shapes financial decision-making in ways distinct from objective knowledge. Under Bounded Rationality, individuals who perceive themselves as financially capable are more likely to engage with financial information and tools (Simon, 2000). This perceived competence may translate into greater scrutiny of AI-generated advice and more cautious behavior in digital financial environments, strengthening the protective effect of AI engagement.

**H4.** *Financial knowledge miscalibration (overconfidence) moderates the relationship between willingness to use AI for financial advice and the likelihood of experiencing financial loss due to fraud.*

Financial knowledge miscalibration, where subjective knowledge exceeds objective knowledge, introduces a distinct mechanism. Overconfident individuals search less for information, rely more on heuristics, and are less likely to heed protective cues (Simon, 1955; Piehlmaier, 2022). When combined with willingness to use AI, these tendencies may be exaggerated such that overconfident users may accept AI-generated financial information with less verification, trusting their ability to distinguish sound from fraudulent advice (Cucinelli & Soana, 2023; Xiao et al., 2022). This reduced circumspection diminishes effective cognitive guardianship, increasing vulnerability to fraud schemes that exploit both digital engagement and miscalibrated expertise.

3. Methods

3.1. Data

This study used data from the 2024 National Financial Capability Study (NFCS), which was funded by the FINRA Investor Education Foundation and conducted by Meridian Research & Insights. The sample consisted of 25,539 adults (aged 18 and older) from across the United States, with approximately 500 respondents from each state, including the District of Columbia. Data collection occurred between June and October 2024. The dataset was weighted using national weights to ensure it accurately reflects the U.S. population by age, gender, ethnicity, and Census Division (FINRA Investor Education Foundation, 2025). Although the full survey included 25,539 adults, the analytic sample was restricted to respondents with valid data on the fraud-loss outcome and the covariates included in each model. The dependent variable was based on the NFCS item asking whether the respondent lost money due to fraud. This question was asked only to respondents who first reported believing they had been targeted by financial fraud in the past year. Among respondents who reported being targeted and provided a valid response (N = 3689), 1644 reported losing money and 2045 did not report losing money 5.

Cases with missing, ‘don’t know,’ or ‘prefer not to say’ responses for all the variables were excluded, and listwise deletion reduced the final analytic sample for Model 1 to 2982 respondents and the analytic samples for Models 2 and 3 to 2956 respondents. Characteristics of the full sample are presented in Table 1.

Table 1. Descriptives for Full Sample.

| Variables                                  |         | N (%)          |
|--------------------------------------------|---------|----------------|
| Willingness to use AI for financial advice | 1 (Yes) | 4986 (19.5%)   |
| Financial Loss due to fraud                | 1 (Yes) | 1644 (6.4%)    |
| Gender                                     | Male    | 12,512 (49.0%) |

Table 1. Cont.

| Variables                      |                                               | N (%)               |
|--------------------------------|-----------------------------------------------|---------------------|
| Marital Status                 | Married                                       | 11,185 (43.8%)      |
|                                | Single                                        | 9567 (37.5%)        |
|                                | Separated                                     | 458 (1.8%)          |
|                                | Divorced                                      | 3056 (12.0%)        |
|                                | Widowed/er                                    | 1272 (5.0%)         |
| Employment Status              | Self-employed                                 | 1916 (7.5%)         |
|                                | Work full-time                                | 9851 (38.6%)        |
|                                | Work part-time                                | 2459 (9.6%)         |
|                                | Homemaker                                     | 1565 (6.1%)         |
|                                | Full-time student                             | 764 (3.0%)          |
|                                | Permanently sick, disabled, or unable to work | 1228 (4.8%)         |
|                                | Unemployed or temporarily laid off            | 2200 (8.6%)         |
| Household Income               | Retired                                       | 5556 (21.8%)        |
|                                | Less than \$15,000                            | 2889 (11.3%)        |
|                                | At least \$15,000 but less than \$25,000      | 2480 (9.7%)         |
|                                | At least \$25,000 but less than \$35,000      | 2637 (10.3%)        |
|                                | At least \$35,000 but less than \$50,000      | 3586 (14.0%)        |
|                                | At least \$50,000 but less than \$75,000      | 4769 (18.7%)        |
|                                | At least \$75,000 but less than \$100,000     | 3431 (13.4%)        |
|                                | At least \$100,000 but less than \$150,000    | 3282 (12.9%)        |
|                                | At least \$150,000 but less than \$200,000    | 1377 (5.4%)         |
| Subjective financial knowledge | At least \$200,000 but less than \$300,000    | 754 (3.0%)          |
|                                | \$300,000 or more                             | 336 (1.3%)          |
|                                | M = 4.89, SD = 1.39                           | Min = 1, Max = 7    |
| Objective financial knowledge  |                                               | M = 3.03, SD = 1.71 |
| Risk tolerance                 |                                               | M = 4.72, SD = 2.67 |
|                                |                                               | Min = 0, Max = 7    |
|                                |                                               | Min = 1, Max = 10   |

### 3.2. Measures

#### 3.2.1. Dependent Variable

**Financial Loss Due to Fraud.** The financial loss due to fraud was operationalized using the survey question, "...Did you lose any money as a result of the fraud or scam?" The responses were coded such that 1 represented "Yes" and 0 represented "No." This variable compares respondents who reported losing money due to fraud with those who reported being targeted but not losing money.

#### 3.2.2. Independent Variables

**Willingness to Use AI for Financial Advice:** This measure was operationalized using the survey question, "Would you be interested in getting financial advice from AI (artificial intelligence)?" The responses were coded similarly, with 1 representing "Yes" and 0 representing "No." While this measure captures stated willingness rather than actual usage, prior research on technology acceptance and fintech adoption suggests that willingness to adopt financial technologies reflects underlying behavioral and cognitive characteristics, including attitudes toward digital financial engagement, trust in algorithmic systems, and openness to technology-mediated decision-making (Davis, 1989; Venkatesh et al., 2003; Dietvorst et al., 2015; D'Acunzio et al., 2019). As such, it serves as a meaningful proxy for behavioral orientation toward AI-enabled financial environments.

**Subjective Financial Knowledge:** Subjective financial knowledge was evaluated using the survey question, "On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall financial knowledge?" To construct the interaction variable while avoiding multicollinearity between the interaction term and its

respective construct, we began by standardizing the measures. Subsequently, we created the interaction term using the z-score of subjective financial knowledge.

**Objective Financial Knowledge:** Objective financial knowledge was assessed by calculating the total score from 7 items designed to gauge participants' actual financial knowledge similar to previous studies (e.g., Brown & Riley, 2025; Ouyang et al., 2025; Pandey et al., 2024). The correct responses to the survey questions (see Appendix A) were scored, with correct answers earning a score of 1 and incorrect answers receiving a score of 0. The total score across the 7 survey items was used to create the objective financial knowledge measure, which ranged from 0 to 7. This score was standardized to create an interaction term and avoid multicollinearity. The interaction term was derived from the Z score of objective financial knowledge.

**Financial Knowledge Miscalibration:** Financial knowledge miscalibration was operationalized as the difference between standardized subjective financial knowledge and standardized objective financial knowledge (ZSFK—ZOFC). Standardizing both subjective and objective financial knowledge ensured these measures were on a common scale, allowing for a meaningful financial knowledge miscalibration measure. Negative values indicated underconfidence, and a score of zero indicated no miscalibration, and any positive value was considered overconfidence (when subjective financial knowledge exceeded objective knowledge). The measure was treated as a continuous predictor for the subsequent analysis. Higher scores reflect greater overconfidence; lower scores reflect greater underconfidence.

### 3.2.3. Covariates

Income, employment status, marital status, gender, and risk tolerance were included as covariates in the analysis. Income ranged from 1 = less than \$15,000 to 10 = \$300,000 or more. Employment status categories included self-employed, employed full-time, employed part-time, homemaker, full-time student, permanently sick/disabled/unable to work, unemployed or temporarily laid off, and retired. Gender was coded as 1 = male and 0 = female. Risk tolerance was measured on a 10-point scale ranging from 1 = not at all willing to take financial risk to 10 = very willing to take financial risk.

### 3.3. Empirical Analyses

To test the hypotheses, this study employed binary logistic regression in IBM SPSS Statistics (Version 31.0) to examine whether willingness to use AI for financial advice is associated with losing money to fraud. Three logistic regression models were estimated. Model 1 included the interaction between standardized objective financial knowledge and willingness to use AI for financial advice. Model 2 included the interaction between standardized subjective financial knowledge and willingness to use AI for financial advice. Model 3 included the interaction between financial knowledge miscalibration and willingness to use AI for financial advice, with all models including covariates. For ease of interpretation, predicted probabilities were computed from the logistic regression models for loss due to fraud (Lost money due to fraud = 1) across selected values of the moderators.

A focused set of demographic covariates, income, employment status, marital status, gender, and risk tolerance, was included because these factors are theoretically linked to financial decision-making (DeLiema et al., 2023; Hussain & Rasheed, 2023) and fraud outcomes. To maintain model parsimony and interpretability (Achen, 2005; Wysocki et al., 2022), not all available demographic variables were included simultaneously. In this sample, education was moderately correlated with income ( $r = 0.448$ ), and age group was also correlated with employment status ( $r = 0.434$ ), suggesting overlap in the information captured by these measures. Given this redundancy and to limit additional sample loss due

to listwise deletion, only the covariates most directly aligned with fraud-related profiles were retained in the models. Statistical significance was assessed using two-tailed tests with  $\alpha = 0.05$ .

## 4. Results

The sample included a slightly higher proportion of females (51%) than males (49%). Participants were more likely to be married (43.8%) than single (37.5%), divorced (12.0%), widowed (5.0%), or separated (1.8%). Regarding household income, at least 45% of participants reported annual income below \$50,000; 45% reported income below \$150,000; and the remaining 10% above \$150,000. On average, subjective financial knowledge was near the midpoint of the scale ( $M = 4.89$ ,  $SD = 1.39$ ), whereas objective financial knowledge was somewhat lower ( $M = 3.03$ ,  $SD = 1.71$ ). Mean risk tolerance was 4.72, indicating relatively lower risk tolerance in this sample. The mean age of participants was 47.86 years.

### 4.1. Bivariate Results

Table 2 presents the distribution of key study variables and demographic characteristics for those who experienced financial loss due to fraud and those who did not. The percentage of respondents who reported being willing to use AI for financial advice differed significantly by fraud-loss status, as indicated by a chi-square test. Mean levels of subjective financial knowledge were higher among respondents who did not report losing money to fraud than among those who did, and this difference was statistically significant based on an independent-samples *t*-test. Objective financial knowledge also differed significantly between groups, with higher mean scores among respondents who did not report losing money to fraud.

**Table 2.** Analytic sample distribution of study variables and demographics by loss due to fraud.

| Variable<br>(N = 3689)                     | Targeted and Lost Money<br>Due to Fraud (N = 1644) | Targeted but Did Not Lose<br>Money Due to Fraud<br>(N = 2045) | Test Statistic                   |
|--------------------------------------------|----------------------------------------------------|---------------------------------------------------------------|----------------------------------|
| Willingness to use AI for financial advice | 560 (34.1)                                         | 439 (21.5)                                                    | $\chi^2 (1) = 73.34, p < 0.001$  |
| Subjective financial knowledge             | 4.79 (1.58)                                        | 5.09 (1.30)                                                   | $t (3648) = -6.24, p < 0.001$    |
| Objective financial knowledge              | 2.76 (1.58)                                        | 3.51 (1.69)                                                   | $t (3687) = -13.79, p < 0.001$   |
| Financial knowledge miscalibration         | 0.07 (1.36)                                        | -0.15 (1.17)                                                  | $t (3648) = 5.47, p < 0.001$     |
| Risk tolerance                             | 5.38 (2.98)                                        | 4.97 (2.61)                                                   | $t (3634) = 4.32, p < 0.001$     |
| Male                                       | 859 (52.3)                                         | 1150 (56.2)                                                   | $\chi^2 (1) = 5.83, p = 0.016$   |
| Marital status                             | —                                                  | —                                                             | $\chi^2 (4) = 103.32, p < 0.001$ |
| Employment status                          | —                                                  | —                                                             | $\chi^2 (7) = 132.24, p < 0.001$ |
| Household income                           | —                                                  | —                                                             | $\chi^2 (9) = 181.83, p < 0.001$ |

Financial knowledge miscalibration differed significantly by fraud-loss status: on average, respondents who lost money to fraud had higher miscalibration scores, indicating overconfidence. Risk tolerance was relatively higher among respondents who reported losing money to fraud, and this mean difference was statistically significant. Gender composition also differed by loss of money due to fraud, with a higher proportion of males among those who did not report loss due to fraud. Finally, chi-square tests indicated significant group differences in marital status, employment status, and household income (Table 2).

#### 4.2. Multivariate Results

Table 3 presents results from three binary logistic regression models predicting loss of money due to fraud. In Model 1, objective financial knowledge (OFK) and its interaction with willingness to use AI for financial advice (AIAdvice) were entered as predictors. The interaction term was not significant. However, OFK was significantly associated with lower odds of losing money to fraud ( $OR = 0.759, p < 0.001$ ). Willingness to use AI for financial advice was also associated with lower odds of losing money to fraud ( $OR = 0.591, p < 0.001$ ) among respondents willing to use AI for financial advice. Retired was the only significant employment category in Model 1 and was associated with lower odds of fraud loss relative to those employed full-time ( $OR = 0.553, p < 0.001$ ). In contrast, risk tolerance was positively related to losing money to fraud ( $OR = 1.056, p < 0.001$ ), indicating that each one-unit increase in risk tolerance was associated with 5.6% higher odds of reporting fraud loss. With respect to marital status, separated individuals ( $OR = 2.257, p < 0.05$ ), divorced individuals ( $OR = 1.421, p < 0.01$ ), and widowed individuals ( $OR = 1.664, p < 0.01$ ) each had higher odds of losing money due to fraud when compared to married individuals. Regarding income, results indicated that not all income categories were significantly associated with fraud loss. Respondents earning less than \$15,000 had the highest odds of losing money to fraud ( $OR = 1.569, p < 0.01$ ). In contrast, respondents with incomes of \$100,000–\$149,999 ( $OR = 0.642, p < 0.01$ ), \$200,000–\$299,999 ( $OR = 0.619, p < 0.05$ ), and \$300,000 or more ( $OR = 0.324, p < 0.01$ ) had significantly lower odds of fraud loss than the reference category (\$50,000 to <\$74,999). The remaining income categories were not statistically significant.

In Model 2, subjective financial knowledge (SFK), willingness to use AI for financial advice, and their interaction were included. Willingness to use AI for financial advice was associated with lower odds of losing money to fraud ( $OR = 0.608, p < 0.001$ ), indicating 39% lower odds of losing money to fraud compared with those unwilling to use AI for financial advice. Higher SFK was associated with lower odds of losing money to fraud ( $OR = 0.820, p < 0.001$ ), indicating approximately 18% lower odds of fraud losses with the increase in SFK. Importantly, the interaction between SFK and willingness to use AI was positive and significant ( $OR = 1.242, p < 0.01$ ), indicating that the association between willingness to use AI and fraud-related monetary loss was strengthened when subjective financial knowledge was considered. Males had higher odds of losing money to fraud ( $OR = 1.198, p < 0.05$ ). The pattern of results for other covariates was generally consistent with Model 1. Specifically, higher risk tolerance and being separated, divorced, or widowed (vs. married) were associated with higher odds of losing money to fraud, and respondents with lower household income (vs. \$50,000 to <\$75,000) also had higher odds of loss of money due to fraud. Similar to Model 1, significant income categories above the reference category had lower odds of fraud related financial loss. Consistent with these results, Figure 1 presents the predicted probability of fraud loss (Lost money due to fraud = 1) at low, mean, and high levels of subjective financial knowledge for respondents who were and were not willing to use AI for financial advice. The resulting plot shows that the probability of fraud loss increases at higher levels of subjective financial knowledge among respondents willing to use AI for financial advice than among those unwilling to use AI for financial advice.

In Model 3, financial knowledge miscalibration and its interaction with willingness to use AI for financial advice were included. Financial knowledge miscalibration was not significantly associated with losing money to fraud. Willingness to use AI for financial advice was associated with lower odds of losing money due to fraud ( $OR = 0.596, p < 0.001$ ). However, the interaction between financial knowledge miscalibration and willingness to use AI was significant and positive ( $OR = 1.162, p < 0.05$ ), suggesting that as overconfidence increased, the association between willingness to use AI for financial advice and the

odds of losing money to fraud also increased. Corresponding to these results, Figure 2 shows the predicted probability of fraud loss (Lost money due to fraud = 1) across low, mean, and high levels of financial knowledge miscalibration. Moving from left to right means a transition from underconfidence to overconfidence. The pattern shows that the predicted probability of fraud loss increases more noticeably as respondents move from underconfidence to overconfidence among those willing to use AI for financial advice. On the contrary, predicted probability was less sharp among those who were not willing to use AI for financial advice.

**Table 3.** Logistic regression results.

| Predictor (vs. Reference)                    | $\beta$       | OR    | 95% CI         | $\beta$       | OR    | 95% CI         | $\beta$                  | OR    | 95% CI         |
|----------------------------------------------|---------------|-------|----------------|---------------|-------|----------------|--------------------------|-------|----------------|
|                                              | Model 1 (OFK) |       |                | Model 2 (SFK) |       |                | Model 3 (Miscalibration) |       |                |
| Interaction terms                            |               |       |                |               |       |                |                          |       |                |
| AIAdvice $\times$ OFK                        | −0.091        | 0.913 | [0.765, 1.090] | —             | —     | —              | —                        | —     | —              |
| AIAdvice $\times$ SFK                        | —             | —     | —              | 0.217 **      | 1.242 | [1.063, 1.452] | —                        | —     | —              |
| AIAdvice $\times$ Miscalibration             | —             | —     | —              | —             | —     | —              | 0.150 *                  | 1.162 | [1.024, 1.318] |
| Main effects                                 |               |       |                |               |       |                |                          |       |                |
| AI Advice (1 vs. 0)                          | −0.527 ***    | 0.591 | [0.494, 0.706] | −0.498 ***    | 0.608 | [0.509, 0.726] | −0.518 ***               | 0.596 | [0.499, 0.712] |
| Objective financial knowledge (z)            | −0.276 ***    | 0.759 | [0.684, 0.842] | —             | —     | —              | —                        | —     | —              |
| Subjective financial knowledge (z)           | —             | —     | —              | −0.199 ***    | 0.820 | [0.743, 0.905] | —                        | —     | —              |
| Financial knowledge miscalibration           | —             | —     | —              | —             | —     | —              | 0.025                    | 1.025 | [0.947, 1.111] |
| Risk tolerance                               | 0.054 ***     | 1.056 | [1.024, 1.088] | 0.058 ***     | 1.060 | [1.027, 1.094] | 0.041 *                  | 1.042 | [1.010, 1.074] |
| Marital status (ref = Married)               |               |       |                |               |       |                |                          |       |                |
| Single                                       | 0.174         | 1.191 | [0.978, 1.449] | 0.180         | 1.197 | [0.984, 1.457] | 0.198 *                  | 1.219 | [1.002, 1.484] |
| Separated                                    | 0.814 *       | 2.257 | [1.205, 4.228] | 0.777 *       | 2.175 | [1.135, 4.167] | 0.870 **                 | 2.387 | [1.253, 4.548] |
| Divorced                                     | 0.351 **      | 1.421 | [1.095, 1.843] | 0.321 *       | 1.378 | [1.063, 1.787] | 0.325 *                  | 1.384 | [1.068, 1.793] |
| Widowed/widower                              | 0.509 **      | 1.664 | [1.136, 2.438] | 0.541 **      | 1.718 | [1.171, 2.520] | 0.549 **                 | 1.731 | [1.183, 2.534] |
| Employment status (ref = Full-time employee) |               |       |                |               |       |                |                          |       |                |
| Self-employed                                | 0.220         | 1.246 | [0.947, 1.638] | 0.200         | 1.222 | [0.928, 1.609] | 0.183                    | 1.200 | [0.913, 1.579] |
| Work part-time                               | −0.030        | 0.970 | [0.735, 1.281] | 0.003         | 1.003 | [0.761, 1.322] | −0.033                   | 0.968 | [0.734, 1.275] |
| Homemaker                                    | 0.222         | 1.249 | [0.838, 1.863] | 0.264         | 1.302 | [0.873, 1.940] | 0.267                    | 1.306 | [0.876, 1.947] |
| Full-time student                            | 0.311         | 1.365 | [0.827, 2.254] | 0.298         | 1.348 | [0.816, 2.227] | 0.319                    | 1.375 | [0.831, 2.275] |
| Permanently sick/disabled                    | 0.099         | 1.104 | [0.756, 1.611] | 0.099         | 1.104 | [0.756, 1.612] | 0.116                    | 1.123 | [0.769, 1.639] |
| Unemployed/laid off                          | 0.019         | 1.019 | [0.740, 1.405] | −0.008        | 0.992 | [0.718, 1.370] | 0.000                    | 1.000 | [0.724, 1.382] |
| Retired                                      | −0.593 ***    | 0.553 | [0.431, 0.708] | −0.653 ***    | 0.521 | [0.406, 0.668] | −0.711 ***               | 0.491 | [0.384, 0.629] |
| Gender (male = 1)                            | 0.142         | 1.153 | [0.975, 1.364] | 0.181 *       | 1.198 | [1.014, 1.416] | 0.177 *                  | 1.193 | [1.010, 1.410] |
| Household income (ref = \$50 k–\$74,999)     |               |       |                |               |       |                |                          |       |                |
| <\$15,000                                    | 0.450 **      | 1.569 | [1.138, 2.164] | 0.576 ***     | 1.778 | [1.294, 2.443] | 0.557 ***                | 1.746 | [1.269, 2.402] |
| \$15 k–\$24,999                              | 0.333 *       | 1.396 | [1.022, 1.906] | 0.453 **      | 1.573 | [1.153, 2.147] | 0.443 **                 | 1.558 | [1.141, 2.126] |
| \$25 k–\$34,999                              | 0.123         | 1.131 | [0.843, 1.519] | 0.194         | 1.214 | [0.905, 1.629] | 0.193                    | 1.212 | [0.904, 1.626] |
| \$35 k–\$49,999                              | 0.131         | 1.140 | [0.858, 1.513] | 0.157         | 1.170 | [0.883, 1.551] | 0.142                    | 1.153 | [0.870, 1.528] |
| \$75 k–\$99,999                              | −0.267        | 0.766 | [0.580, 1.011] | −0.264        | 0.768 | [0.583, 1.012] | −0.286 *                 | 0.751 | [0.570, 0.990] |
| \$100 k–\$149,999                            | −0.443 **     | 0.642 | [0.479, 0.861] | −0.511 ***    | 0.600 | [0.448, 0.804] | −0.536 ***               | 0.585 | [0.437, 0.784] |
| \$150 k–\$199,999                            | −0.227        | 0.797 | [0.538, 1.181] | −0.373        | 0.688 | [0.464, 1.022] | −0.394                   | 0.675 | [0.455, 1.001] |
| \$200 k–\$299,999                            | −0.480 *      | 0.619 | [0.384, 0.997] | −0.588 *      | 0.555 | [0.347, 0.890] | −0.622 *                 | 0.537 | [0.335, 0.860] |
| ≥\$300,000                                   | −1.128 **     | 0.324 | [0.147, 0.712] | −1.132 **     | 0.322 | [0.147, 0.708] | −1.186 **                | 0.306 | [0.139, 0.672] |
| Constant                                     | −0.247        | 0.781 | —              | −0.327        | 0.721 | —              | −0.207                   | 0.813 | —              |
| Nagelkerke R <sup>2</sup>                    | 0.153         |       |                | 0.138         |       |                | 0.137                    |       |                |
| −2 Log Likelihood                            | 3638.51       |       |                | 3633.80       |       |                | 3637.00                  |       |                |
| n                                            | 2982          |       |                | 2956          |       |                | 2956                     |       |                |

Note. Reference categories for categorical predictors were selected as the categories with the highest frequency in the sample. 95% confidence intervals are shown in brackets.  $p < 0.05 = *$ ,  $p < 0.01 = **$ ,  $p < 0.001 = ***$ .

Among covariates, risk tolerance remained positively associated with losing money to fraud (OR = 1.042,  $p < 0.05$ ). Compared with married respondents, those who were single, separated, divorced, or widowed had higher odds of losing money to fraud, and males had higher odds of losing money to fraud than females (OR = 1.193,  $p < 0.05$ ). Finally, respondents earning lower income continued to show higher odds of losing money to fraud relative to the income category of at least \$50,000 but less than \$75,000 and income categories of at least \$75,000 but less than \$100,000 and above had lower odds of losing money to fraud compared to the income category of at least \$50,000 but less than \$75,000.

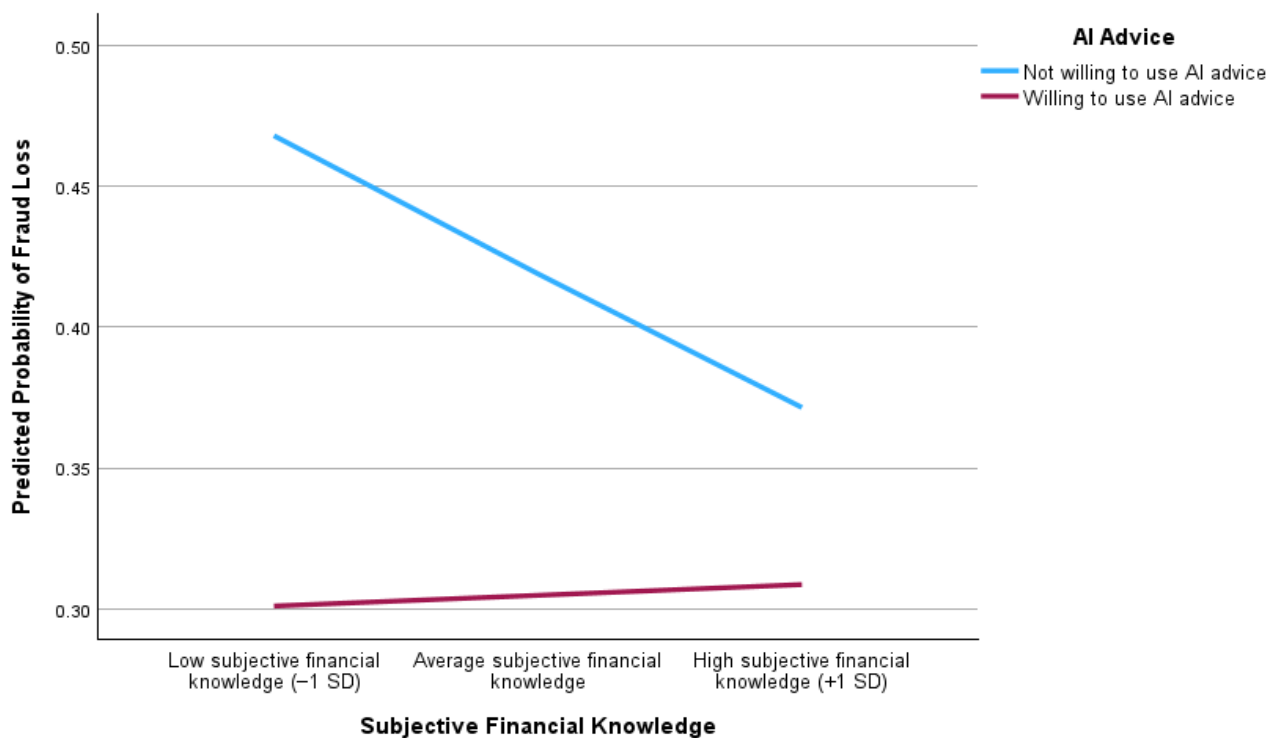


**Figure 1.** Predicted probability of fraud loss by willingness to use AI for financial advice and subjective financial knowledge.

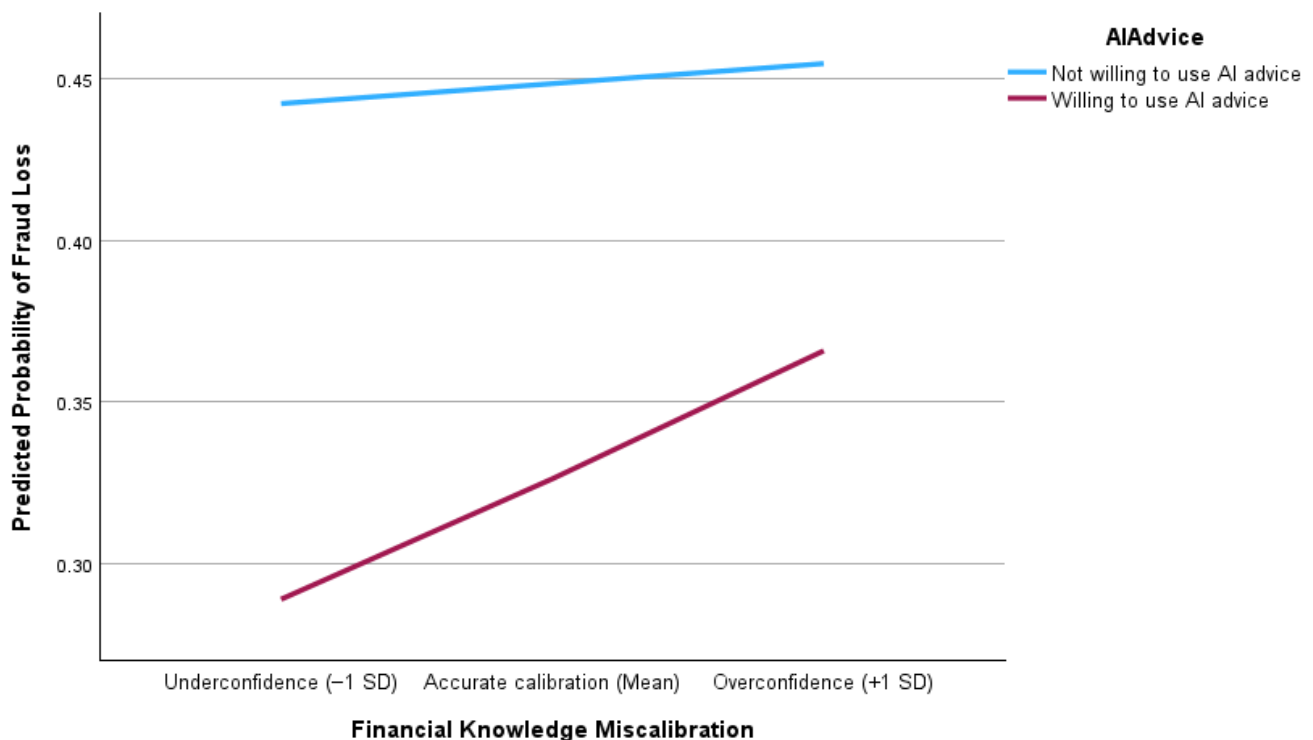


**Figure 2.** Predicted probability of fraud loss by willingness to use AI for financial advice and financial knowledge miscalibration.

#### Robustness Check and Diagnostics

In Model 1, the objective financial knowledge variable was included as a predictor; the model fit, as assessed by the Hosmer–Lemeshow goodness-of-fit test, was not significant,  $\chi^2(8) = 4.789$ ,  $p = 0.780$ , indicating acceptable model fit. Additionally, the collinearity

diagnostics did not suggest multicollinearity, given VIF values ranging from 1.05 to 1.74. Assessment of standardized residuals and Cook's distance indicated no evidence that the results were driven by some highly unusual or influential observations (largest standardized residual = 2.06; Cook's distance = 0.13).

Furthermore, we estimated a reduced model including only the interaction term, willingness to use AI, and objective financial knowledge. The interaction remained statistically non-significant in this reduced specification (OR = 0.963, 95% CI [0.812, 1.143],  $p = 0.668$ ). However, the Hosmer–Lemeshow test indicated poorer fit for the reduced model,  $\chi^2(8) = 16.867$ ,  $p = 0.032$ , whereas the fully adjusted model demonstrated acceptable fit. In the same model, we further adjusted for education and race/ethnicity. The interaction between willingness to use AI and objective financial knowledge remained negative and statistically non-significant (OR = 0.905, 95% CI [0.757, 1.082],  $p = 0.275$ ). The Hosmer–Lemeshow test was not significant,  $\chi^2(8) = 10.687$ ,  $p = 0.220$ , indicating acceptable model fit.

In the second logistic regression model, the interaction between willingness to use AI and subjective financial knowledge was positive and statistically significant (OR = 1.242, 95% CI [1.063, 1.452],  $p = 0.006$ ). The Hosmer–Lemeshow goodness-of-fit test was not significant,  $\chi^2(8) = 10.405$ ,  $p = 0.238$ , suggesting acceptable model fit. Collinearity diagnostics also did not suggest problematic multicollinearity, with VIF values ranging from 1.05 to 1.73. In addition, standardized residuals and Cook's distance also suggested that the results were not driven by some influential observations (largest standardized residual = 1.99; Cook's distance = 0.12).

As an additional robustness check, we estimated a reduced model that included only the main interaction term, willingness to use AI, and subjective financial knowledge. The interaction remained positive and statistically significant in this reduced model (OR = 1.343, 95% CI [1.159, 1.557],  $p < 0.001$ ). However, the Hosmer–Lemeshow test indicated poorer fit for the reduced model ( $\chi^2(7) = 24.854$ ,  $p < 0.00$ ). Additionally, we estimated an expanded model that included education and race/ethnicity as controls. The interaction between AI advice use and subjective financial knowledge remained positive and statistically significant (OR = 1.246, 95% CI [1.063, 1.460],  $p = 0.007$ ). The Hosmer–Lemeshow test was not significant ( $\chi^2(8) = 8.981$ ,  $p = 0.344$ ), indicating acceptable model fit.

In the model including the interaction between willingness to use AI and financial knowledge miscalibration, the interaction term was positive and statistically significant (OR = 1.162, 95% CI [1.024, 1.318],  $p = 0.020$ ). Additional diagnostics supported the adequacy of the final model. The Hosmer–Lemeshow goodness-of-fit test was not significant,  $\chi^2(8) = 14.603$ ,  $p = 0.067$ , indicating acceptable fit. Collinearity diagnostics also did not indicate problematic multicollinearity, with VIF values ranging from 1.04 to 1.76. Assessment of standardized residuals and Cook's distance further suggested that the reported association was not driven by some influential observations (largest standardized residual = 2.04; largest Cook's distance = 0.06).

As a specification check, we estimated a reduced model including only the interaction between AI advice use and financial knowledge miscalibration, along with the corresponding main effects. The interaction remained positive and statistically significant (OR = 1.143, 95% CI [1.014, 1.289],  $p = 0.029$ ). However, the Hosmer–Lemeshow test showed poorer fit for the reduced model,  $\chi^2(8) = 15.915$ ,  $p = 0.044$ . As an additional robustness check, we estimated a more expanded model that included education and race/ethnicity controls. The interaction between willingness to use AI and financial knowledge miscalibration remained positive and statistically significant (OR = 1.184, 95% CI [1.041, 1.346],  $p = 0.010$ ). The Hosmer–Lemeshow test was not significant,  $\chi^2(8) = 12.209$ ,  $p = 0.142$ , indicating acceptable model fit.

Overall, the robustness checks and diagnostic tests suggest that the final model results are broadly comparable across the reduced and expanded specifications. In addition, the final models passed the diagnostic tests. These findings suggest that the main results are not highly sensitive to the removal or addition of covariates. Accordingly, we retain the final model as the preferred specification, because its results are consistent across models and the diagnostic checks indicate no multicollinearity issues or influential cases that would meaningfully affect the findings.

## 5. Discussion

This study contributes to the literature at the intersection of financial technology adoption and consumer financial vulnerability by providing evidence that willingness to engage with AI for financial advice is systematically related to fraud-related financial outcomes. Importantly, the findings demonstrate that this relationship is not uniform but depends on individuals' cognitive characteristics, particularly the alignment between perceived and actual financial knowledge.

The research examined the relationship between willingness to use AI for financial advice and the likelihood of experiencing financial loss due to fraud. This focus aligns with the financial well-being framework proposed by Brüggen et al. (2017), which identifies technological factors, such as digitalization, fintech, and innovations in financial services, such as robo-advisors, as important contextual determinants of financial well-being. In this context, examining the association between willingness to use AI for financial advice seeking and fraud loss is consistent with the framework. The study further extends this perspective by examining the moderating roles of objective financial knowledge, subjective financial knowledge, and financial knowledge miscalibration (i.e., overconfidence).

The results supported Hypothesis 1, which posited that willingness to use AI for financial advice was negatively associated with the likelihood of experiencing financial loss due to fraud. AI-enabled tools can help detect and prevent fraud, which may partially explain this negative association (Bello & Olufemi, 2024; Faulhaber & Chaffin, 2024; Sun et al., 2025). Another possible explanation is that greater willingness to use AI for financial advice may reflect higher digital literacy, which could reduce vulnerability to fraud losses. Consistent with this, digital literacy can have a protective effect against fraud victimization, particularly in the context of online fraud (Li et al., 2024). It is important to note that the findings focus specifically on willingness to use AI for financial advice seeking and its association with financial loss due to fraud.

Contrary to Hypothesis 2, the association between willingness to use AI for financial advice and financial loss due to fraud was not significantly moderated by objective financial knowledge. Although the interaction term was negative in direction, it was not statistically significant, indicating that the strength of the relationship between willingness to use AI for financial advice and fraud loss did not differ meaningfully across levels of objective financial knowledge. However, the main effect of objective financial knowledge was negatively associated with financial loss due to fraud, showing that lower objective financial knowledge is linked to greater vulnerability to fraud losses (Bar Lev et al., 2022; Cucinelli & Soana, 2023; Engels et al., 2021; Kadoya et al., 2021; Zhu et al., 2023).

Interestingly, the relationship between the willingness to use AI for financial advice and financial loss due to fraud was moderated both by subjective financial knowledge and financial knowledge miscalibration, which supports H<sub>3</sub> and H<sub>4</sub>. Findings related to miscalibration as a moderator were consistent with prior studies, which found that overconfident individuals were more likely to become victims of financial fraud (Cucinelli & Soana, 2023). Overconfident individuals may rely more heavily on heuristic processing and exhibit reduced information search (Porto & Xiao, 2016), which can increase suscep-

tibility to fraudulent cues, particularly in technology-mediated financial environments. Individuals with this characteristic may also place trust in tools and technologies that confirm their beliefs, leading to less scrutiny of financial opportunities presented to them. Overconfidence bias may play a role in underestimating risk or overestimating a person's ability to detect fraud, thereby increasing vulnerability to fraud. In contrast, results showed that as subjective financial knowledge increases, the odds of becoming a victim of financial fraud are lower. These results do not align with those of [Xiao et al. \(2022\)](#), who found that subjective financial knowledge was positively associated with the risk of investment fraud. This could be explained by differences in context: [Xiao et al. \(2022\)](#) focused on investment fraud, whereas the current study examined broader fraud loss outcomes.

Results for the covariates included in the study were generally consistent across each of the models. Higher risk tolerance was associated with a greater likelihood of financial loss due to fraud across all three models. Similarly, compared to married individuals, respondents in all other marital status categories had higher odds of experiencing fraud related financial loss, with the exception of single respondents who were significant only in Model 3. Retired individuals had lower odds of losing money to fraud than full-time employees across all three models, aligning with prior research (e.g., [Bar Lev et al., 2022](#)) that finds most victims of financial fraud are employed. Gender was also significant in Models 2 and 3, with males showing greater odds of losing money due to fraud, consistent with prior studies ([Bar Lev et al., 2022](#)). This finding suggests that gender differences in financial self-perceptions are associated with vulnerability to financial fraud.

Across income categories, respondents in the lower-income groups (vs. \$50,000 to <\$75,000) had higher odds of reporting a financial loss due to fraud. This pattern aligns with prior evidence that individuals with fewer financial resources and greater financial insecurity are more likely to engage in scams and experience monetary losses ([DeLiema et al., 2019](#)). Consistent with this broader pattern, national survey evidence also shows that lower-income adults are more likely than upper-income adults to report having lost money due to an online scam or attack ([Gottfried et al., 2025](#)).

The findings carry several results driven implications for financial educators, fraud-prevention practitioners, and policymakers. For financial educators, the most consequential finding is that the accuracy of financial self-assessment matters. The main effect of objective financial knowledge was negatively associated with fraud loss across all three models, confirming that financial education programs that improve actual financial knowledge are likely to reduce fraud loss vulnerability. However, the interaction between subjective financial knowledge and willingness to use AI suggests that how individuals feel about their financial acumen also shapes fraud outcomes, particularly in the context of AI use. Financial educators should then incorporate calibration training into existing curricula to help learners compare their self-assessed financial knowledge against their actual knowledge and reflect on the gaps ([Xiao et al., 2022](#)). Curricula designed for active users of digital financial tools should place particular emphasis on financial knowledge calibration, as this subgroup may be most vulnerable when overconfidence is present.

For fraud prevention practitioners and consumer advocacy organizations, the significant interaction between financial knowledge miscalibration and willingness to use AI identifies a specific segment with a targetable higher risk profile: consumers who are willing to use AI for financial advice and who overestimate their financial knowledge. Outreach campaigns aimed at this segment should focus not on discouraging AI use, which is overall associated with lower fraud loss, but rather should focus on reducing decision-making shortcuts. Consistent with guidance from the Association of Certified Fraud Examiners ([ACFE, 2024](#)), practitioners should promote verification behaviors such as pausing before acting on unsolicited financial offers, independently confirming the

identity of financial advisors or AI-generated recommendations, and using fraud-reporting tools before transferring funds (“Stop, Verify, and Confirm”). These behavioral prompts directly counteract the high heuristic and low scrutiny decision-making that characterizes overconfident individuals interacting with technology-mediated financial environments.

For policymakers, the finding that willingness to use AI is negatively associated with fraud loss, but that financial knowledge miscalibration lessens this protection, has implications for how AI financial tools are designed and regulated. Platforms providing AI generated financial advice could be required or incentivized to incorporate mechanisms that interrupt fast, low-effort decision-making at key transaction points, such as prompted confirmation steps, plain-language risk disclosures, or automated alerts when user behavior deviates from established patterns. Policymakers might also consider requiring AI financial advisory platforms to include fraud awareness prompts, similar to disclosure requirements for investments, that are triggered when users appear to be acting on unsolicited advice or making more risky transactions. Such design interventions would extend the guardianship function that AI already provides in fraud detection (Sun et al., 2025) into the realm of consumer fraud prevention.

Finally, the income-related findings deserve attention. Respondents earning below \$50,000 annually had higher odds of fraud loss relative to the reference income group across all three models. Lower-income consumers, who may have fewer financial buffers and limited access to professional financial advice, represent a particularly vulnerable group. Fraud prevention resources, such as lower cost financial counseling, digital literacy programming, and access to AI tools, should be prioritized in community settings serving lower-income populations, where the consequences of fraud loss can be the most devastating and where recovery is often difficult.

Overall, these findings contribute to the literature by demonstrating that willingness to use AI for financial advice is associated with lower odds of financial losses from fraud. We further extend prior work by showing that the relationship between the willingness to use AI and loss due to fraud depends on individuals’ perceptions of their financial knowledge. The current study is grounded in bounded rationality and routine activity theory to examine whether the willingness to use AI for financial advice is associated with financial losses due to fraud, and to examine how subjective financial knowledge and financial knowledge miscalibration moderate this relationship. By combining these perspectives, we extend the application of bounded rationality and routine activity theory to the emerging context of financial advice seeking using AI and financial fraud susceptibility.

### 5.1. Limitations

While this study provides new insights into willingness to use AI for financial advice and financial loss due to fraud, the findings should be interpreted with caution due to several limitations. First, the data used in this study are cross-sectional, which limits causal inference and prevents establishing temporal ordering among the variables. Similarly important is the potential for endogeneity in the relationship between willingness to use AI for financial advice and fraud outcomes. While the analysis treats willingness to adopt AI as a behavioral characteristic associated with fraud exposure, it is possible that prior experiences with fraud may influence individuals’ openness to alternative financial tools. Second, the analytic sample was restricted to respondents who answered the question about losing money to fraud, and the responses such as “don’t know” and “prefer not to say” were excluded. As a result, the final sample size was reduced, potentially affecting the generalizability of the findings. Third, key constructs were measured using self-reported responses, which may be subject to recall error and social desirability bias. In addition, our measure captures willingness to use AI rather than actual use of specific AI. AI tools were

still in relatively early use when the survey question on willingness to use AI was asked in 2024. As a result, respondents may have based their answers more on expectations about AI than on actual experience with AI tools, and the role of AI in 2024 may differ from its role in 2026. The fraud measure was broad and did not differentiate between types or mediums (e.g., online vs. offline), and it relied on subjective assessments (Lin et al., 2025), limiting nuanced interpretations. Respondents might have erroneously misclassified legitimate losses as fraud, affecting their responses. Fourth, although relevant covariates were included, unobserved factors (e.g., digital literacy) may still influence the observed relationships.

## 5.2. Future Research

Future research should address the limitations of the current study and extend this work by using longitudinal data to strengthen causal inference and establish the temporal ordering of the key variables. Future studies should also use larger samples to improve the generalizability of the findings. In addition, measures of willingness to use AI should be complemented or replaced with indicators of actual AI use for financial advice seeking, and fraud-related outcomes should be more specific (e.g., online, telecom) to allow for more accurate interpretation. To further triangulate the findings, researchers could incorporate qualitative approaches, such as open-ended survey questions or interviews, to enhance understanding of how and why financial advice seeking using AI may relate to losses due to fraud. Finally, future work should include additional contextual variables (e.g., digital skills, prior fraud exposure, personal finance technology usage) to better identify the conditions under which these relationships are most likely to occur.

## 6. Conclusions

This study examined the association between willingness to use AI for financial advice and financial loss due to fraud using a nationally representative sample of U.S. adults from the 2024 National Financial Capability Study. Drawing on Routine Activity Theory and Bounded Rationality, we proposed that willingness to use AI for financial advice would function as a behavioral characteristic shaping exposure to fraud risk and the capacity to recognize and respond to fraudulent schemes.

Results from multivariate logistic regression models supported this expectation. Willingness to use AI for financial advice was associated with lower odds of experiencing financial loss due to fraud across all three models. The relationship between willingness to use AI and fraud-related financial loss was moderated by subjective financial knowledge and financial knowledge miscalibration (overconfidence), but not by objective financial knowledge. Specifically, miscalibration amplified the positive association between willingness to use AI and fraud-related loss, while higher subjective financial knowledge was associated with lower odds of loss.

These findings carry practical implications for financial educators, professionals, and policymakers. Efforts to reduce vulnerability to fraud losses should address financial knowledge levels as well as the accuracy of individuals' self-assessments of that knowledge. Overconfident consumers who are willing to engage with AI financial tools may represent a particularly high-risk group warranting targeted outreach.

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## Appendix A

**Table A1.** Survey Questions on Objective Financial Knowledge.

| Questions                                                                                                                                                                                                                               | Response Options                                                                                                                                                                                                                                                               |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1<br>Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?                                                | <ul style="list-style-type: none"> <li>• More than \$102</li> <li>• Exactly \$102</li> <li>• Less than \$102</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul>                                                                                                     |
| 2<br>Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?                                              | <ul style="list-style-type: none"> <li>• More than today</li> <li>• Exactly the same</li> <li>• Less than today</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul>                                                                                                  |
| 3<br>If interest rates rise, what will typically happen to bond prices?                                                                                                                                                                 | <ul style="list-style-type: none"> <li>• They will rise</li> <li>• They will fall</li> <li>• They will stay the same</li> <li>• There is no relationship between bond prices and the interest rate</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul>               |
| 4<br>Suppose you owe \$1000 on a loan and the interest rate you are charged is 20% per year compounded annually. If you did not pay anything off, at this interest rate, how many years would it take for the amount you owe to double? | <ul style="list-style-type: none"> <li>• Less than 2 years</li> <li>• At least 2 years but less than 5 years</li> <li>• At least 5 years but less than 10 years</li> <li>• At least 10 years</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul>                     |
| 5<br>Which of the following indicates the highest probability of getting a particular disease?                                                                                                                                          | <ul style="list-style-type: none"> <li>• There is a one-in-twenty chance of getting the disease</li> <li>• 2% of the population will get the disease</li> <li>• 25 out of every 1000 people will get the disease</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul> |
| 6<br>A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.                                                                         | <ul style="list-style-type: none"> <li>• True</li> <li>• False</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul>                                                                                                                                                   |
| 7<br>Buying a single company's stock usually provides a safer return than a stock mutual fund.                                                                                                                                          | <ul style="list-style-type: none"> <li>• True</li> <li>• False</li> <li>• Don't know</li> <li>• Prefer not to say</li> </ul>                                                                                                                                                   |

## References

- Achen, C. H. (2005). Let's put garbage-can regressions and garbage-can probits where they belong. *Conflict Management and Peace Science*, 22(4), 327–339. [[CrossRef](#)]

- Association of Certified Fraud Examiners. (n.d.). *Fraud 101: What is fraud?* Available online: <https://www.acfe.com/fraud-resources/fraud-101-what-is-fraud> (accessed on 6 February 2026).
- Association of Certified Fraud Examiners. (2024). *Occupational fraud 2024: A report to the nations*. Available online: <https://www.acfe.com/-/media/files/acfe/pdfs/rtnn/2024/2024-report-to-the-nations.pdf> (accessed on 6 February 2026).
- Bagherifam, N., Naghdi, S., Ahmadian, V., Fazlzadeh, A., & Baghalzadeh Shishehgharkhaneh, M. (2025). Digital regulatory governance: The role of RegTech and SupTech in transforming financial oversight and administrative capacity. *International Journal of Financial Studies*, 13(4), 217. [CrossRef]
- Bar Lev, E., Maha, L. G., & Topliceanu, S. C. (2022). Financial frauds' victim profiles in developing countries. *Frontiers in Psychology*, 13, 999053. [CrossRef]
- Beals, M., DeLiema, M., & Deevy, M. (2015). *Framework for a taxonomy of fraud*. Stanford Center on Longevity & FINRA Investor Education Foundation. Available online: <https://longevity.stanford.edu/wp-content/uploads/2016/03/Full-Taxonomy-report.pdf> (accessed on 6 February 2026).
- Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in fintech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, 119(7), 1411–1430. [CrossRef]
- Bello, O. A., & Olufemi, K. (2024). Artificial intelligence in fraud prevention: Exploring techniques and applications, challenges, and opportunities. *Computer Science & IT Research Journal*, 5(6), 1505–1520. [CrossRef]
- Britt, S. L., Canale, A., Fernatt, F., Stutz, K., & Tibbetts, R. (2015). Financial stress and financial counseling: Helping college students. *Journal of Financial Counseling and Planning*, 26(2), 172–186. [CrossRef]
- Brown, E. H., & Riley, K. (2025). When (financial) knowledge isn't power: How race disrupts financial literacy's relationship to health precarity. *Sociology Compass*, 19(9), e70115. [CrossRef]
- Brüggen, E. C., Hogreve, J., Holmlund, M., Kabadayi, S., & Löfgren, M. (2017). Financial well-being: A conceptualization and research agenda. *Journal of Business Research*, 79, 228–237. [CrossRef]
- Burnes, D., Henderson, C. R., Jr., Sheppard, C., Zhao, R., Pillemer, K., & Lachs, M. S. (2017). Prevalence of financial fraud and scams among older adults in the United States: A systematic review and meta-analysis. *American Journal of Public Health*, 107(8), e13–e21. [CrossRef]
- CFP Board. (2015, April 13). *Stress test: Americans, especially women and younger people, stressed by finances*. CFP Board. Available online: <https://www.cfp.net/news/2015/04/stress-test-americans-especially-women-and-younger-people-stressed-by-finances> (accessed on 6 February 2026).
- Chang, C.-Y. M., Park, S., & Dinh, M. C. (2026). Advice by algorithms: Dual dimensions of trust in AI financial service adoption. *Journal of Retailing and Consumer Services*, 88, 104537. [CrossRef]
- Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 44(4), 588–608. [CrossRef]
- COSO & Association of Certified Fraud Examiners. (2023). *Fraud risk management guide* (2nd ed.). ACFE.
- Cucinelli, D., & Soana, M. G. (2023). Are financially illiterate individuals all the same? A study on incorrect and “do not know” answers to financial knowledge questions. *International Journal of Bank Marketing*, 41(4), 697–726. [CrossRef]
- D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of robo-advising. *The Review of Financial Studies*, 32(5), 1983–2020. [CrossRef]
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. [CrossRef] [PubMed]
- DeLiema, M., Deevy, M., Lusardi, A., & Mitchell, O. S. (2020). Financial fraud among older Americans: Evidence and implications. *The Journals of Gerontology: Series B*, 75(4), 861–868. [CrossRef] [PubMed]
- DeLiema, M., Fletcher, E., Kieffer, C. N., Mottola, G. R., Pessanha, R., & Trumpower, M. (2019, September). *Exposed to scams: What separates victims from non-victims?* Stanford Center on Longevity, FINRA Investor Education Foundation, & BBB Institute for Marketplace Trust. Available online: [https://www.finrafoundation.org/sites/finrafoundation/files/exposed-to-scams-what-separates-victims-from-non-victims\\_0\\_0.pdf](https://www.finrafoundation.org/sites/finrafoundation/files/exposed-to-scams-what-separates-victims-from-non-victims_0_0.pdf) (accessed on 6 February 2026).
- DeLiema, M., Li, Y., & Mottola, G. (2023). Correlates of responding to and becoming victimized by fraud: Examining risk factors by scam type. *International Journal of Consumer Studies*, 47(3), 1042–1059. [CrossRef]
- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114–126. [CrossRef]
- Engels, C., Kumar, K., & Philip, D. (2021). Financial literacy and fraud detection. In J. O. S. Wilson, G. A. Panos, & C. Adcock (Eds.), *Financial literacy and responsible finance in the FinTech era: Capabilities and challenges* (pp. 124–146). Routledge. [CrossRef]
- Fan, J. X., & Yu, Z. (2022). Prevalence and risk factors of consumer financial fraud in China. *Journal of Family and Economic Issues*, 43(2), 384–396. [CrossRef]
- Faulhaber, E., & Chaffin, C. (2024). Artificial intelligence in accounting, medicine, and law with potential implications for financial planning: A review of literature. *Financial Services Review*, 32(4), 1–11. [CrossRef]

- Federal Trade Commission. (2024). *Consumer sentinel network data book 2024*. Available online: [https://www.ftc.gov/system/files/ftc\\_gov/pdf/csn-annual-data-book-2024.pdf](https://www.ftc.gov/system/files/ftc_gov/pdf/csn-annual-data-book-2024.pdf) (accessed on 6 February 2026).
- Federal Trade Commission. (2025, March 10). *New FTC data show a big jump in reported losses to fraud to \$12.5 billion in 2024*. Available online: <https://www.ftc.gov/news-events/news/press-releases/2025/03/new-ftc-data-show-big-jump-reported-losses-fraud-125-billion-2024> (accessed on 6 February 2026).
- FINRA Investor Education Foundation. (2025). *2024 national financial capability study*. Available online: <https://finrafoundation.org/national-financial-capability-study> (accessed on 6 February 2026).
- FINRA Investor Education Foundation & AARP Fraud Watch Network. (2022). *Blame and shame in the context of financial fraud: A movement to change our societal response to a rampant and growing crime*. Available online: <https://www.finrafoundation.org/sites/finrafoundation/files/Blame-and-Shame-in-the-Context-of-Financial-Fraud.pdf> (accessed on 6 February 2026).
- Golladay, K. A., & Snyder, J. A. (2023). Financial fraud victimization: An examination of distress and financial complications. *Journal of Financial Crime*, 30(6), 1606–1628. [CrossRef]
- Gottfried, J., Park, E., & Anderson, M. (2025, July 31). *Online scams and attacks in America today*. Pew Research Center. Available online: <https://www.pewresearch.org/internet/2025/07/31/online-scams-and-attacks-in-america-today/> (accessed on 6 February 2026).
- Hermann, E., & Alberhasky, M. (2025). The trusted partner for financial decision making: Romantic partner or AI? *Computers in Human Behavior*, 177, 108877. [CrossRef]
- Hollis-Peel, M. E., Reynald, D. M., Van Bavel, M., Elffers, H., & Welsh, B. C. (2011). Guardianship for crime prevention: A critical review of the literature. *Crime, Law and Social Change*, 56(1), 53–70. [CrossRef]
- Hussain, S., & Rasheed, A. (2023). Risk tolerance as mediating factor in individual financial investment decisions: A developing-country study. *Studies in Economics and Econometrics*, 47(2), 185–198. [CrossRef]
- Isaia, E., Oggero, N., & Sandretto, D. (2024). Is financial literacy a protection tool from online fraud in the digital era? *Journal of Behavioral and Experimental Finance*, 44, 100977. [CrossRef]
- Jung, D., Dorner, V., Weinhardt, C., & Puzmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, 28(3), 367–380. [CrossRef]
- Kadoya, Y., Khan, M. S. R., Narumoto, J., & Watanabe, S. (2021). Who is next? A study on victims of financial fraud in Japan. *Frontiers in Psychology*, 12, 649565. [CrossRef]
- Li, P., Li, Q., & Du, S. (2024). Does digital literacy help residents avoid becoming victims of frauds? Empirical evidence based on a survey of residents in six provinces of east China. *International Review of Economics & Finance*, 91, 364–377. [CrossRef]
- Lin, J. T., Bumcrot, C., Valdes, O., Mottola, G., Sarver, S., Ganem, R., Kieffer, C., & Walsh, G. (2025). *Investors in the United States: A report of the National Financial Capability Study*. FINRA Investor Education Foundation. Available online: <https://www.finrafoundation.org/InvestorReport2024> (accessed on 6 February 2026).
- Lloyds Banking Group. (2024). *What is the emotional impact of fraud?* Available online: <https://www.lloydsbankinggroup.com/insights/what-is-the-emotional-impact-of-fraud.html> (accessed on 6 February 2026).
- Mastercard. (2025). *\$362 billion in fraud: How insights can help reduce losses and improve the digital experience*. Available online: <https://www.mastercard.com/global/en/news-and-trends/Insights/2025/362-billion-in-fraud-how-insights-can-help-reduce-losses-and-improve-the-digital-experience.html> (accessed on 6 February 2026).
- Miró, F. (2014). Routine activity theory. In J. M. Miller (Ed.), *The encyclopedia of theoretical criminology*. Wiley. [CrossRef]
- Ngai, E. W., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems*, 50(3), 559–569. [CrossRef]
- Ouyang, C., Crandall, T., & Chatterjee, S. (2025). The impact of the COVID-19 income shock on debt management: A mediation analysis. *Financial Services Review*, 33(1), 1–27. [CrossRef]
- Pandey, S., Guillemette, M. A., & Asebedo, S. D. (2024). Human capital and pandemic-related stimulus usage. *Financial Planning Review*, 7(2), e1178. [CrossRef]
- Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: Why overconfident investors drive the expansion of automated financial advice. *Financial Innovation*, 8(1), 14. [CrossRef]
- Podaná, Z. (2017). Violent victimization of youth from a cross-national perspective: An analysis inspired by routine activity theory. *International Review of Victimology*, 23(3), 325–340. [CrossRef]
- Porto, N., & Xiao, J. J. (2016). Financial literacy overconfidence and financial advice seeking. *Journal of Financial Service Professionals*, 70(4), 78–88.
- Pratt, T. C., & Turanovic, J. J. (2016). Lifestyle and routine activity theories revisited: The importance of “risk” to the study of victimization. *Victims & Offenders*, 11(3), 335–354. [CrossRef]
- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99–118. [CrossRef]
- Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, 63(2), 129–138. [CrossRef]
- Simon, H. A. (2000). Bounded rationality in social science: Today and tomorrow. *Mind & Society*, 1(1), 25–39. [CrossRef]

- Sun, G., Ling, Z., Li, Y., & Xie, C. (2025). Artificial intelligence and financial fraud. *Pacific-Basin Finance Journal*, 93, 102830. [CrossRef]
- Suzuki, A., Shikata, K., & Shimada, T. (2025). Patterns and predictors of cyber fraud victimization: Testing routine activity theory and general theory of crime in Japan. *Journal of Economic Criminology*, 9, 100186. [CrossRef]
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. [CrossRef]
- Wilder, M. (2025, January). *Top 5 fraud trends of 2025*. ACFE Insights Blog. Available online: <https://www.acfe.com/acfe-insights-blog/blog-detail?s=top-fraud-trends-2025> (accessed on 6 February 2026).
- Williams, W. (2025, September 2). Survey: Consumers increasingly turn to AI for financial advice. *ABA Banking Journal*. Available online: <https://bankingjournal.aba.com/2025/09/survey-consumers-increasingly-turn-to-ai-for-financial-advice/> (accessed on 6 February 2026).
- Wysocki, A. C., Lawson, K. M., & Rhemtulla, M. (2022). Statistical control requires causal justification. *Advances in Methods and Practices in Psychological Science*, 5(2). [CrossRef]
- Xiao, X., Li, X., & Zhou, Y. (2022). Financial literacy overconfidence and investment fraud victimization. *Economics Letters*, 212, 110308. [CrossRef]
- Zhu, H., Pysander, E. L. S., & Söderberg, I. L. (2023). Not transparent and incomprehensible: A qualitative user study of an AI-empowered financial advisory system. *Data and Information Management*, 7(3), 100041. [CrossRef]
- 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. [CrossRef]

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