

Explaining Auditors' Intentions to Use Artificial Intelligence for Financial Statement Fraud Detection: An Extended Technology Acceptance Model

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ABSTRACT

The advent of digitization has transformed the auditing paradigm, compelling auditors to integrate technology into their practices. However, the use of artificial intelligence (AI) in auditing and fraud detection remains modest. Therefore, this study explores Algerian auditors' intentions to use AI for detecting accounting manipulation in financial statements. To achieve this, we expanded the technology acceptance model by incorporating three additional constructs: Trust in AI outputs, AI fraud detection-related knowledge and AI self-efficacy. A convenience sample of 162 auditors was surveyed, and the data were analyzed using Hierarchical multiple regression. The findings indicate that AI-related knowledge, perceived usefulness, trust, ease of use, and AI self-efficacy significantly positively associated with auditors' intentions to adopt AI. This research aims to offer valuable insights for stakeholders on how to encourage audit practitioners to embrace AI technology.

Keywords: AI-related knowledge, AI self-efficacy, trust in AI outputs, financial statement manipulation, AI-based auditing Management

INTRODUCTION

Fraud and manipulation of financial statements pose a threat to the integrity of economic activities and have negative repercussions for various market participants (Hacini et al., 2025; Leeroy et al., 2026). Yet, detecting such fraud remains a challenge for all stakeholders. The proliferation of artificial intelligence (AI) technologies has brought additional challenges to the accounting and auditing profession, alongside the many advantages associated with its use. For example, AI tools have been used to detect errors, manipulation, and fraud (Ali et al., 2022; Hajek & Henriques, 2017), but conversely, this technology has also been used to learn and practice manipulation and fraud (Okoro et al., 2023). This indicates that AI is a double-edged sword: on the one hand, it effectively contributes to detecting and predicting the likelihood of illegal financial and accounting practices; on the other hand, it may help develop the skills and capabilities of corrupt individuals. The researchers emphasized the need to integrate digital technology solutions to track and detect fraud and account manipulation (Odufisan et al., 2025; Raza & Suryawati, 2026).

According to Public Company Accounting Oversight Board (PCAOB), "the auditor has a responsibility to plan and perform the audit to obtain sufficient appropriate audit evidence for the auditor to obtain reasonable assurance about whether the financial statements are free of material misstatement, whether due to fraud or error". Previous investigations show that auditors' AI intentions rise with willingness to learn, perceived usefulness (PU),

perceived ease of use (PEOU), and trust in AI (Mansour et al., 2025; Gui et al., 2025; Rahmanet et al., 2025). Data-specific IT knowledge was the most critical adoption factor for internal audit analytics (Islam & Stafford, 2022). Furthermore, AI knowledge was the strongest determinant of AI usage intention in managerial accounting (Cuc et al., 2025b). AI self-efficacy has also been found to be an important determinant of AI technology acceptance (Çelik Demirci et al., 2026). These findings suggest that AI acceptance in the auditing profession is influenced by a range of psychological and professional variables.

In fact, many studies have praised the effectiveness of AI-powered auditing in detecting irregularities, fraud and financial corruption (Zangana et al., 2026). Current studies have focused on developing models to aid in detecting financial fraud using AI tools such as machine learning (Hajek & Henriques, 2017; Kapoor et al., 2027; Odufisan et al., 2025; Okoro et al., 2023), deep learning algorithms (Craja et al., 2020; Leeroy et al., 2026), predictive data analytics (Gkegkas et al., 2025), and big data analytics (Aboud & Robinson, 2022) in various economic contexts, including Brazil, Nigeria, Ireland, and the United States. Other studies have attempted to develop AI-based frameworks, such as reinforcement learning, to improve the ability to detect fraud and manipulation in financial statements (e.g., Chen et al., 2026; Hacini et al., 2025). Furthermore, some researchers have conducted reviews of the literature related to the uses of AI in the field of financial fraud detection (Ali et al., 2022; Gkegkas et al., 2025; Goel & Rajpoot, 2024; Panigrahi & Gorle, 2026; Triyanto & Ali, 2026; Yang et al., 2026), and most of the previous reviews and research have indicated the need for more investigations in this field, especially in developing countries, such as Algeria, where we did not find any previous study in this context.

Whilst the classic TAM constructs of PU and PEOU are good at capturing general attitudes towards a system (Davis, 1989), they are frequently inadequate in explaining adoption in high risk, specialist environments such as auditing (Mansour et al., 2025). Financial statement fraud detection (FSFD) is a high liability, high cognitive demand and opaque (black box) environment. The model is therefore extended by the inclusion of trust in AI output, AI fraud detection related knowledge and AI self efficacy. Trust in AI output is relevant to the black box and reliability issues inherent in fraud analytics (Gui et al., 2025; Rahman et al., 2025). AI fraud detection related knowledge is relevant to the domain specific knowledge required to make sense of the outputs (Mansour et al., 2025). AI self efficacy is relevant to the auditor's own confidence in their ability to carry out the audit task using the AI (Commerford et al., 2024). The extended model thus provides a more complete explanation of the relationships between these various dimensions and the auditor's behavioural intentions. The study also provides context specific empirical findings from Algeria which add to the body of literature on digital auditing adoption in emerging economies.

Based on the above, this study addresses the following research questions: RQ1: To what extent do PEOU, PU, trust in AI outputs, AI fraud detection-related knowledge, and AI self-efficacy associated with auditors' intentions to use AI for FSFD? RQ2: To what extent does extending the TAM with trust, AI-related knowledge, and AI self-efficacy improve its ability to explain variance in auditors' intentions to use AI for FSFD? Accordingly, this study extends TAM by incorporating three AI- and auditing-specific factors.

LITERATURE REVIEW AND RESEARCH HYPOTHESES

Financial statement fraud

Fraud is "an intentional act that results in a material misstatement in financial statements that are the subject of an audit" (PCAOB, 2026). It encompasses all forms of deliberate omission, concealment, misrepresentation, or manipulation that distort financial/accounting information for known or unknown purposes, and may have a negative impact on certain parties. Fraud detection is "a challenging task because of the low number of known fraud cases" (Craja et al., 2020, p.6). With its increasing prevalence, financial statement fraud has become a major concern and obsession for stakeholders such as investors, shareholders, owners, auditing firms, insurance companies, lenders, and government agencies such as tax authorities (Craja et al., 2020; Hacini et al., 2025; Hajek & Henriques, 2017). FSFD is "crucial for sustaining capital market stability, protecting investor confidence, and reducing systemic risks" (Chen et al., 2026). Gkegkas et al. (2025) stressed that traditional auditing procedures "often fail to detect" complex and tightly concealed manipulation and fraud in financial reports and statements. Craja et al. (2020) stated that combining "financial and textual data" strengthens the likelihood of detecting financial statement fraud.

AI-powered Auditing

The use of these technologies is no longer limited to large organizations; it has become available to small and medium-sized enterprises (SMEs) and even individuals to perform their professional and personal tasks. In recent years, organizations have accelerated the integration of various AI technologies into their different functions, including internal control, auditing, accounting, marketing, and human resources (Raza & Suryawati, 2026). During these years, researchers have rushed to develop working models based on the latest artificial intelligence technologies to help detect financial fraud (Chen et al., 2026; Hacini et al., 2025). Previous research has revealed that trust, usefulness, ease of use, and willingness to learn have emerged as key drivers for the use of AI in auditing (Gui et al., 2025; Mansour et al., 2025; Rahman et al., 2025).

Raza and Suryawati (2026) concluded that the efficient use of AI tools enhances the ability to detect financial fraud, reduce risks, and improve decision-making. Qader and Cek (2024) revealed that the application of blockchain and AI technologies has a positive impact on audit quality and enhances opportunities for fraud detection, leading to improved financial reporting quality. Similarly, Zangana et al. (2026) indicated that adopting AI in forensic accounting increases the chances of detecting anomalies, manipulation, and financial fraud. Gkegkas et al. (2025) concluded that employing predictive analytics in auditing not only enhances the ability to detect fraud but also works proactively to prevent it. Yuluce et al. (2026) also pointed out that fraud has become more complex and stressed the need to employ AI-supported auditing systems to improve the ability to detect and prevent financial fraud early. However, despite recent literature documenting the benefits of adopting AI systems in the process of detecting fraud in financial statements and reports, several challenges may limit their effectiveness, including the ability and willingness of auditors themselves to engage in this approach (Qatawneh, 2025). In this context, however, Odufisan et al. (2025) pointed out that the challenges of AI-assisted fraud detection include a lack of technologies and the absence of a regulatory and legal framework.

RESEARCH HYPOTHESES

Perceived Ease of Use (PEOU)

PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). Triyanto and Ali (2026) pointed out that the use of AI systems to detect financial fraud faces challenges as a result of the diversity of company characteristics and the complexity of fraudulent activities across different sectors. It is well known that fraudsters constantly change their methods and devise new ones as soon as their existing ones are discovered, which can complicate the tasks of auditors, especially novices. Existing literature indicates that PEOU of AI systems and software improves perceptions of their usefulness and generates intentions to use them for various purposes and tasks (e.g., Al Wael et al., 2024; Aljabri & Al-Ansi, 2024; Choung et al., 2025; Gui et al., 2025; Mouloudj et al., 2026). Therefore, auditors' perception of AI's ease of use is expected to contribute to positive intentions toward its application in financial statement audits and the verification of accounting information. Accordingly, we develop the following hypothesis:

H1: PEOU positively associated with auditors' intention to use AI for FSFD.

Perceived Usefulness (PU)

PU refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). In their literature review, Yuluce et al. (2026) noted that integrating various AI technologies significantly improves the speed and accuracy of detecting and preventing financial fraud. Odufisan et al. (2025) stated that the benefits of AI-assisted fraud detection include "increased efficiency, improved accuracy, and proactive risk mitigation". Most current TAM-based research generally assumes that PU enhances technology acceptance (Choung et al., 2025; Mouloudj et al., 2026). However, the role of PU in using AI in the context of FSFD remains insufficiently explored in the literature. Choung et al. (2023) found that the PU was affected by PEOU, and influenced attitudes and intentions to use AI. Prior studies have consistently shown that PU is linked to intentions to use digital technologies (Al Wael et al., 2024; Aljabri & Al-Ansi, 2024; Gui et al., 2025; Makhoulouf &

Mouloudj, 2024; Mouloudj et al., 2026), as they reduce effort and cost. By this logic, auditors are likely to engage with AI for fraud detection if they perceive its advantages. Therefore, we can hypothesize the following:

H2: PU positively associated with auditors' intention to use AI for FSFD.

Trust in AI Outputs

In the age of AI, trust in its outputs has become a pivotal driver in AI-based behaviors. Users are expected to accept AI systems when they feel they can provide tailored responses that meet their expectations (Bach et al., 2024; Lee & Cha, 2025). Trust is defined as "the belief that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" (Bach et al., 2024, p.1256). In the context of our study, trust in AI refers to auditors' belief that the information provided by the AI system regarding fraud detection in financial statements is reliable and accurate. Hunsicker et al. (2026) indicated that the accuracy of AI outputs improves trust and willingness to engage in behavior, and that interpreting outputs helps in detecting errors and is important if the outputs are inaccurate.

Ha and Kim (2024) found that textual interpretations enhance trust in AI compared to visual interpretations, and that these interpretations are important for decision-making and evaluating the quality of AI outputs. Several studies have pointed to the importance of trust in shaping user attitudes and willingness to embrace AI-powered services in various settings (e.g., Helen et al., 2026; Rahman et al., 2025; Wang et al., 2026; Zhou & Lu, 2025). Furthermore, Choung et al. (2023) reported that trust in AI has an important impact on the intention to use AI, through the PU and attitude of users. However, Helen et al. (2026) noted that research has documented conflicting results regarding the relationship between digital trust and the acceptance of AI technologies. Therefore, this study hypothesized as follows.

H3: Trust in AI Outputs positively associated with auditors' intention to use AI for FSFD.

AI Fraud Detection-Related Knowledge

AI systems can analyze vast amounts of data with high precision, identifying patterns and anomalies that may indicate manipulative behaviors (Qader & Cek, 2024). However, the success and effectiveness of using AI depends on auditors having sufficient knowledge of this technology. While previous investigations have consistently documented the relationship between AI-related knowledge and behavioral intentions for using AI-powered services (e.g., Cuc et al., 2025b; Islam et al., 2022), research, to the best of our knowledge, has not examined the role of AI fraud detection-related knowledge in driving auditors' willingness to adopt it. Mansour et al. (2025) found that willingness to learn AI was positively related to actual AI use in auditing. Some studies have indicated that AI knowledge can exert a direct or indirect influence on the acceptance of AI technology (Çelik Demirci et al., 2026; Cuc et al., 2025a; Cuc et al., 2025b; Huynh-Thanh et al., 2026; Islam et al., 2022; Mouloudj et al., 2026; Torroba-Díaz et al., 2025). Thus, we hypothesized as follows.

H4: AI fraud detection-related knowledge positively associated with auditors' intention to use AI for FSFD.

AI Self-Efficacy

AI self-efficacy refers to perceived ability to use AI technologies/products, often measured through assistance, comfort with AI, anthropomorphic interaction, and technological skills (Çelik Demirci et al., 2026). Commerford et al. (2024) pointed out that auditors may be unprepared to use some AI algorithms, especially when they feel less control over the process. Kokina et al. (2025) indicated that the most prominent challenges of using AI include transparency, explainability, bias, reliability, and the fear of auditors overreliance on AI. Some studies have revealed that technology readiness and self-efficacy were linked to PU and PEOU, and those perceptions mediated adoption (Damerji & Salimi, 2021; Zhao et al., 2025). It is expected that AI self-efficacy will contribute to users feeling more confident in their abilities and increasing their desire to learn more, which in turn supports the intention and actual use of AI tools (Damerji & Salimi, 2021; Lee & Cao, 2025; Rahman et al., 2025). Thus, we hypothesized as follows.

H5: AI self-efficacy positively associated with auditors' intention to use AI for FSFD.

METHODOLOGY

Measurement Instrument

This study used a self-administered paper questionnaire to collect primary data from respondents. The first section included demographic information such as gender, age group, professional experience, and education. The second section contained questionnaire items adapted from previous investigations to suit the context of the current study. In particular, PU and PEOU were measured using items adapted from Davis (1989), Al Wael et al. (2024), and Choung et al. (2023). Trust in AI outputs was measured using items derived from Choung et al. (2023). AI fraud detection-related knowledge was adapted from Mouloudj et al. (2026). AI self-efficacy and intention to use AI was measured using item adapted from Al Wael et al. (2024), Choung et al. (2023) and Qatawneh (2025). The five-point Likert scale was used (strongly disagree to strongly agree). The questionnaire was developed in English and translated into Arabic by a professional translator. Two experts in auditing and digital technology were invited to review the questionnaire items, and based on their feedback, some statements were modified and improved. A pilot study was conducted with 24 respondents to verify the ease of understanding of the questionnaire items and to exclude or revise any ambiguous items. All items were clear enough. **Table 1** shows the questionnaire items.

Table 1. Items and Statements

Constructs	Items	Statements
Perceived Ease of Use (PEOU)	PEOU1	Learning to use AI tools for financial statement fraud detection would be straightforward for me.
	PEOU2	I believe interacting with AI systems for fraud detection would require little effort.
	PEOU3	It would be easy for me to become skillful in using AI fraud detection tools.
Perceived Usefulness (PU)	PU1	Using AI would improve my effectiveness in detecting financial statement fraud during audit engagements.
	PU2	AI would enhance the quality and accuracy of my fraud detection decisions.
	PU3	Using AI would increase my productivity when identifying potential financial statement fraud.
Trust in AI Outputs (TAIO)	TAIO1	I believe AI-generated fraud detection results are generally accurate and dependable for audit purposes.
	TAIO2	I would trust AI outputs when assessing potential financial statement fraud risks.
	TAIO3	I believe AI provides reliable recommendations that can support my professional audit judgments.
AI Fraud Detection-Related Knowledge (AIFDK)	AIFDK1	I understand how AI technologies can assist auditors in detecting financial statement fraud.
	AIFDK2	I am familiar with the capabilities and limitations of AI-based fraud detection systems.
	AIFDK3	I possess sufficient knowledge to evaluate AI applications used for financial statement fraud detection.
AI Self-Efficacy (AISE)	AISE1	I am confident in my ability to learn AI tools for financial statement fraud detection.
	AISE2	I believe I can effectively use AI systems to support fraud detection activities.
	AISE3	I feel capable of solving problems encountered while using AI-based fraud detection systems.
Intention to Use AI (ITU)	ITU1	I intend to use AI technologies whenever appropriate for financial statement fraud detection.
	ITU2	I expect to use AI systems regularly during future financial statement audit engagements.
	ITU3	I will actively adopt AI technologies to improve financial statement fraud detection in my work.

Participants and Procedure

As there was no comprehensive public register of practising auditors available we were unable to construct a probability sampling frame and so resorted to a convenience sample. Respondents were drawn from professional and institutional contacts within the audit firms in the five Algerian cities of Algiers, Boumerdès, Tizi Ouzou, Blida and Tipaza, from professional events and from a mailing list of the professional association. Any practitioner involved in audit work was eligible to participate and no other screening criteria were applied. We used a sample of 240 respondents. The questionnaire was distributed between March and May 2026. We received 173 responses, and after manual sorting, nine were discarded due to incompleteness. Therefore, 162 copies remained acceptable

(response rate of 67.50%). Respondents were informed of the survey objectives before completing the questionnaire, and that participation was voluntary, anonymous, and posed no physical or financial risk. The questionnaire was distributed in person, and respondents were asked to either answer immediately or to leave it for later. Completing the questionnaire took approximately ten minutes. All respondents gave their verbal consent and institutional ethical consent was not required according to the country's regulations because the survey was anonymous and did not expose respondents to any kind of risk.

Table 2 presents the demographic characteristics of the 162 respondents. The sample comprised 55.56% males and 44.44% females. Regarding age, 19.14% respondents were aged 18–30 years, 34.57% were aged 31–40 years, 32.10% were aged 41–50 years, and 14.20% were above 50 years. In terms of professional experience, 8.64% respondents had 1–5 years of experience, 31.48% had 6–10 years, 37.65% had 11–15 years, and 22.22% had more than 15 years. Regarding education, 16.67% respondents had a high school education or less, 40.12% held a tertiary diploma or bachelor's degree, 23.46% had a professional certification, and 19.75% held a master's or doctoral degree.

Table 2. Demographic Profile of the Sample (n=162)

Characteristic	Variables	Frequency	%
Gender	Male	90	55.56
	Female	72	44.44
Age (years)	18-30	31	19.14
	31-40	56	34.57
	41-50	52	32.10
	Above 50	23	14.20
Experience (years)	1-5	14	08.64
	6-10	51	31.48
	11-15	61	37.65
	Above 15	36	22.22
Education	High school level or less	27	16.67
	Tertiary (Diploma/bachelor)	65	40.12
	Professional certification	38	23.46
	Master's/Doctorate	32	19.75

Source: Authors' own work

RESULTS

Descriptive Analysis

Table 3 presents the descriptive statistics and internal consistency estimates for the six study constructs. The mean scores ranged from 3.497 (AI fraud detection-related knowledge) to 3.829 (PEOU). Cronbach's alpha coefficients ranged from 0.785 to 0.891, exceeding the commonly recommended minimum threshold of 0.70, indicating acceptable internal consistency. The skewness values ranged from -0.249 to 0.058, and kurtosis values ranged from -0.592 to -0.117. All values fall comfortably within the commonly accepted -1.5 to +1.5 range for both skewness and kurtosis (Makhlouf & Mouloudj, 2024), suggesting no substantial departures from normality.

Table 3. Descriptive statistics

Constructs	Mean	Std. Dev.	Cronbach's Alpha	Skewness	Kurtosis
PEOU	3.829	0.627	0.849	-0.249	-0.209
PU	3.740	0.652	0.820	-0.014	-0.319
Trust in AI Outputs	3.693	0.683	0.891	-0.145	-0.592
AIFDK	3.497	0.613	0.808	0.058	-0.203
AI Self-Efficacy	3.652	0.635	0.823	0.024	-0.431
Intention to Use AI	3.689	0.603	0.785	-0.058	-0.117

Note: "AIFDK" AI fraud detection-related knowledge

Source: Authors' own work

Discriminant and Convergent Validity

Discriminant validity was examined using the "Fornell–Larcker criterion", which requires the square root of each construct's "average variance extracted" (AVE) to exceed its correlations with all other constructs (Fornell & Larcker, 1981). As **Table 4** shows, the diagonal values, ranging from 0.838 to 0.907, are greater than every corresponding off-diagonal correlation, so each construct shares more variance with its own indicators than with any other construct. This is the case for the constructs whose conceptual proximity is greatest: intention correlates more strongly with PU ($r = 0.434$) and trust ($r = 0.415$) than with PEOU ($r = 0.349$) or self-efficacy ($r = 0.343$). Convergent validity was assessed through the AVE, which exceeded 0.70 for all six constructs, indicating that each construct explains more than 70% of the variance in its indicators and comfortably surpassing the 0.50 threshold (Fornell & Larcker, 1981). The constructs are therefore both internally consistent and empirically separable.

Table 4. Construct correlations, discriminant validity (Fornell-Larcker) and AVE results

Constructs	1	2	3	4	5	6	AVE
1. PEOU	0.875^a						0.766
2. PU	0.215**	0.856					0.733
3. Trust	0.309**	0.290**	0.907				0.822
4. AIFDK	0.085	0.280**	0.182*	0.850			0.722
5. AI Self-Efficacy	0.202**	0.323**	0.268**	0.136*	0.859		0.738
6. Intention	0.349**	0.434**	0.415**	0.394**	0.343**	0.838	0.702

Note: ^a Diagonal values (in bold) represent the square root of AVE. "AIFDK" AI fraud detection-related knowledge. * $p < 0.05$; ** $p < 0.01$.

Source: Authors' own work

Because all variables were collected through a single self-report questionnaire, common method bias is a potential concern. Procedurally, we mitigated it by keeping constructs conceptually distinct, varying item wording and anchors, and assuring respondents of anonymity. Together with the discriminant validity evidence in **Table 4**, in which no construct correlation exceeds 0.44 and each construct's AVE square root exceeds all of its correlations, these results suggest that common method bias is unlikely to threaten the findings.

Hypothesis Testing

Hierarchical multiple regression was performed to test the hypotheses and to assess the incremental contribution of the added constructs. Before testing the hypotheses, the assumptions of multiple regression were examined. Multicollinearity was assessed using tolerance and "variance inflation factor" (VIF) values. Tolerance ranged from 0.797 to 0.954 and VIF from 1.048 to 1.254 across both models (see **Table 5**), well within the conventional thresholds of tolerance > 0.10 and VIF < 5 criterion, indicating that multicollinearity is not a concern (Hair et al., 2017). The Durbin–Watson statistic (1.845) was close to 2, indicating no autocorrelation (Durbin & Watson, 1950).

TAM's core constructs (PEOU, PU) were entered in Model 1 and the three added constructs in Model 2. **Table 5** reports the results. In Model 1, PEOU ($\beta = 0.258$, $p < 0.001$) and PU ($\beta = 0.348$, $p < 0.001$) were significantly positively associated with intention, explaining 25.70% of its variance, $F(2, 159) = 27.489$, $p < 0.001$. In Model 2, PEOU ($\beta = 0.183$, $p < 0.01$), PU ($\beta = 0.196$, $p < 0.01$), trust in AI outputs ($\beta = 0.184$, $p < 0.01$), AI fraud detection-related knowledge ($\beta = 0.259$, $p < 0.001$) and AI self-efficacy ($\beta = 0.137$, $p < 0.05$) were all significant, supporting H1–H5. The five constructs explained 39.80% of the variance, $F(5, 156) = 20.641$, $p < 0.001$.

The increase in explanatory power was tested formally. The addition of the three constructs raised R^2 from 0.257 to 0.398, $\Delta R^2 = 0.141$, $F\text{-change}(3, 156) = 12.201$, $p < 0.001$, indicating that the extension of TAM contributes significant incremental variance beyond its core beliefs.

Table 5. Hypothesis Testing

Constructs	β	<i>t</i> values	<i>p</i> values	Tolerance	VIF
(Constant)	1.398	4.416	0.000		-
PEOU	0.258	3.831	0.000	0.954	1.048
PU	0.348	5.376	0.000	0.954	1.048
Model 1: $F = 27.489$ ($p < 0.001$); $R^2 = 0.257$					
(Constant)	0.166	0.468	0.641		-
PEOU	0.183	2.872	0.005	0.879	1.138
PU	0.196	3.047	0.003	0.797	1.254
Trust in AI Outputs	0.184	3.040	0.003	0.821	1.218
AIFDK	0.259	4.034	0.000	0.909	1.101
AI Self-Efficacy	0.137	2.150	0.033	0.854	1.171
Model 2: $F = 20.641$ ($p < 0.001$); $R^2 = 0.398$					

Source: Authors' own work

DISCUSSION

We empirically tested all intention to use AI antecedents proposed in our model and confirmed their significant associated with intention to use AI for FSFD. As key components within the TAM (Davis, 1989), PEOU and PU were strongly positively correlated with the intention to use AI for FSFD. This means that the level of auditors' engagement in employing AI in fraud detection depends on their perception of its ease of use and benefits. These benefits include improved capacity, speed, and accuracy in detecting irregularities (such as intentional errors, manipulation, and fraud) (Gkegkas et al., 2025; Qatawneh, 2025; Yuluze et al., 2026; Zangana et al., 2026). This aligns with most previous studies indicating that both PEOU and PU shape behavioral readiness to engage with technology (Aljabri & Al-Ansi, 2024; Davis, 1989; Gui et al., 2025; Mouloudj et al., 2026). Accordingly, PEOU and PU are expected to foster positive attitudes and increase the desire to learn best practices for fraud detection using AI tools. In practice, users often compare the effort expended with the expected benefit of adopting digital technologies. If they perceive the gains (such as reduced time and effort and improved quality) as greater than the costs, their intention to engage is likely to increase.

Furthermore, empirical results have revealed that trust in AI outputs associated with intentions to use AI for fraud detection. This suggests that auditors will be more willing to adopt AI technology in their auditing process if they have strong confidence in the results it provides. Trust in AI is regarded as "knowledge-based trust, indicating trust based on previous experiences of trustor-trustee interactions" (Lee & Cha, 2025, p.8087). In practice, trust in the outputs of an AI system can be fostered if it can provide logical justifications, explanations, and interpretations, rather than simply delivering abstract information based on complex algorithms (Ha & Kim, 2024; Hunsicker et al., 2026; Lee & Cha, 2025). Recent research suggests that the main trust barriers are "opacity, bias, reliability concerns, and overreliance risk", rather than simply a rejection of AI as an advanced technology (Kokina et al., 2025; van Liempd et al., 2025; Li & Goel, 2025). In their review of the literature on trust in AI, Bach et al. (2024) emphasized that trust is influenced by social, ethical, technical, design, and user characteristics. This finding supports the results of several previous investigations that have documented a correlation between trust in AI-powered work environments and behavioral intentions to adopt AI technology (Choung et al., 2023; Gui et al., 2025; Helen et al., 2026; Rahman et al., 2025; Wang et al., 2026; Zhou & Lu, 2025). In some cases, auditors may need to use manual/traditional inspection methods to ensure the accuracy and validity of AI outputs. If the results are positive, they will feel reassured and their doubts about AI's ability to provide credible outputs will disappear, and this will undoubtedly make them more confident in the technology used.

In addition, the findings revealed that auditors' knowledge of AI technology associated with their intention to leverage AI tools for detecting financial statement fraud and AI-related knowledge is the strongest predictor. This suggests that auditors' acquisition of sufficient knowledge about how to use AI systems to detect potential fraud can significantly enhance their intention to use them. In the age of AI, general knowledge about how to use AI is no longer a problem, especially among educated groups. However, the specialized use of AI technology, such as detecting financial fraud, manipulation, and corruption, still faces challenges related to the required skill level and knowledge (Qader & Cek, 2024; Qatawneh, 2025). This finding aligns with previous research demonstrating that knowledge of how to use AI is a key driver of usage intentions (Çelik Demirci et al., 2026; Cuc et al., 2025a; Huynh-

Thanh et al., 2026; Mouloudj et al., 2026; Torroba-Díaz et al., 2025). AI knowledge can support acceptance by enhancing confidence, perceived value, and attitudes (Cuc et al., 2025a; Cuc et al., 2025b; Torroba-Díaz et al., 2025). In fact, many accounting and auditing practitioners in general, and auditors in particular, need to learn more about the optimal use of AI software due to the rapid advancements in this field.

Finally, the results confirmed that AI self-efficacy helps auditors intend to use AI when it translates into feeling capable, seeing AI as easier to use, and feeling less psychological resistance. Higher self-efficacy makes AI seem more usable and valuable, which supports adoption (Damerji & Salimi, 2021; Zhao et al., 2025). Furthermore, greater self-efficacy reduces hesitation and resistance, making adoption more likely (Lee & Cao, 2025; Montag et al., 2023). Li and Goel (2025) revealed that AI reliance was higher for inexperienced auditors, harder tasks, familiar tools, and cognitive congruence; senior auditors were more concerned about skills loss. Indeed, factors such as transparency, explainability, bias, reliability, and fear of hallucinations may hinder the adoption of AI-assisted auditing (Kokina et al., 2025), suggesting that auditors need specialized training to boost AI self-efficacy and reduce these concerns.

CONCLUSIONS

This study examined auditors' intentions to use AI for FSFD by extending the TAM with trust in AI outputs, AI fraud detection-related knowledge, and AI self-efficacy. The findings indicate that all five proposed factors significantly and positively associated with auditors' intentions to use AI, supporting all hypotheses. The results demonstrate that auditors' willingness to adopt AI depends not only on its PEOU and PU but also on their trust in AI-generated outputs, knowledge of AI applications for fraud detection, and confidence in their ability to use such technologies. By integrating these factors, the study provides a broader perspective on AI acceptance in auditing and highlights the importance of both technological and individual capabilities. The findings offer useful implications for audit firms and professional bodies seeking to facilitate responsible AI adoption and strengthen AI-supported financial statement fraud detection practices.

Practical Implications

The findings provide several practical implications for auditing practitioners, audit firms, and professional bodies. Since PU and PEOU significantly influence auditors' intentions to use AI for FSFD, audit firms should provide user-friendly AI tools alongside practical training that demonstrates their benefits for audit efficiency and fraud detection. The significant effect of trust in AI outputs highlights the importance of adopting reliable, transparent. Explainable AI systems, enabling auditors to understand and evaluate AI-generated results before incorporating them into professional judgments. Furthermore, enhancing auditors' AI fraud detection-related knowledge through continuous professional development can facilitate effective technology adoption. Finally, strengthening auditors' AI self-efficacy through hands-on training, workshops, and supervised practice can increase their confidence in using AI technologies. Finally, professional accounting and auditing bodies can support these efforts by developing AI-related competency frameworks and training standards.

Limitations and Future Directions

Beyond its implications, this study has several limitations. First, the study employed a convenience sampling technique and focused on 162 respondents, which may limit the generalizability of the findings to the population under study, countries, or institutional contexts. Future research could employ probability sampling and larger samples across different regions and countries. Second, the study relied on a self-administered questionnaire and self-reported intentions, which may not fully reflect auditors' actual AI usage behavior. Future studies could examine actual adoption and longitudinal usage patterns. Third, the current study relied on the TAM; other theories and models (such as combining planned behavior theory with TAM) could provide stronger evidence. Fourth, the extended TAM incorporated only three additional factors (trust, AI-related knowledge, and AI self-efficacy). Future research could consider other relevant factors, such as perceived risk, explainability, organizational support, AI ethics, and professional judgment. Comparative studies across different auditing environments would also strengthen the evidence.

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