

AI ADOPTION AND FRAUD DETECTION: THE MODERATING ROLE OF AUDITOR EXPERTISE

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Abstract

The growing complexity of financial fraud and rapid digitization of financial reporting have accelerated artificial intelligence (AI) adoption in auditing. The purpose of this study is to examine the impact of AI adoption on fraud detection effectiveness and the moderating role of auditor expertise between AI adoption and fraud detection effectiveness in Pakistan. Primary data were collected through a structured questionnaire from auditors employed by accounting firms recognized by ICAP, including Big Four, internationally affiliated and local firms. Of 670 questionnaires distributed, 550 were returned and 418 valid responses were retained after eliminating incomplete responses. The Purposive sampling technique was employed. The proposed relationships were tested by using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4. The result of measure model validated satisfactory reliability, convergent and discriminant validity. The results of structural model indicate that AI adoption significantly and positively influences fraud detection effectiveness. Moreover, auditor expertise significantly strengthens this relationship, indicating an expertise-amplification effect. These findings propose that Artificial Intelligence technologies and auditor expertise function as complementary capabilities rather than substitutes one. This study contributing to the emerging economy literature on AI-enabled auditing and provides practical implications to audit firms, regulators and accounting educators seeking to improve fraud detection and the effective implementation of AI in Pakistan economy.

1. INTRODUCTION

1.1 Background

The rapid worldwide corporate digital transformation has significantly increased the volume, complexity and velocity of financial data flows, representation of audit processes become more complex and more challengeable. These developments highlighting the limitations of

traditional auditing which usually depend on sample techniques, manual operations and on the human being judgments. As firms adopt increasingly sophisticated information systems, the methods of fraud have also changed. IAASB stresses the need for auditors to integrate artificial intelligence tools in t audit processes to enhance efficiency and bolster public trust. AI technologies

such as ML (machine learning) algorithms, NLP (natural language processing), predictive analytics and NN (neural networks) be responsible for auditors with dominant tools to analyze large data sets quickly (Issa et al., 2016; Rozario & Vasarhelyi, 2018). Nevertheless, the artificial intelligence adoption varies across audit firms and industries as well. While large multinational firms such as big 4 have heavily invested in AI-driven platforms, most small and medium-sized firms appearance several difficulties to AI adoption such as high implementation costs, lack of training the auditors and confrontation or resistance to technological adjustment (Tiron-Tudor & Deliu, 2022). Moreover, even if the AI tools are available to auditor, it depend upon the ability of auditors to apply them effectively. Generally, specialized bodies such as IFAC (the International Federation of Accountants) give emphasis to that the future of auditing depend on technology-driven approaches, noticing that it is important for auditors improve their digital skills to conduct high-quality audits in today's digital environment. Likewise, Pakistan's audit environment is undergoing rapid change, with regulators such as the SECP and SBP increasingly promoting digital reporting and technology-enhanced audits.

1.2 Problem Statement

In spite of rapid adoption of artificial intelligence (AI) in auditing, uncertainty remains regarding its influence on audit outcomes and the conditions under which AI can effectively enhance fraud detection. Auditor expertise may play an important role because auditors with limited expertise may face difficulties in interpreting and appropriately applying AI-generated information (Commerford et al., 2022; Hady & Mudhaffar, 2025). This problem is mainly relevant in emerging economies such as Pakistan, where technological readiness and professional expertise may vary across auditors and firms. Existing research has largely examined AI adoption, fraud detection effectiveness, and auditor expertise as separate dimensions, resulting in fragmented evidence. Moreover, limited empirical research

has examined how auditors interpret AI outputs, develop trust, and incorporate AI-generated information into professional judgment (Anwar & Akeel, 2026). Therefore, an integrated empirical model is required to study the effect of AI adoption on fraud detection effectiveness and determine whether auditor expertise strengthens this relationship, particularly within the Pakistani auditing context.

1.3 Research Questions

- Does Artificial Intelligence adoption improve fraud detection effectiveness in audit engagements?
- Does auditor expertise moderate the relationship between AI adoption and audit outcome?

1.4 Research Objectives

- To evaluate the impact of AI adoption on fraud detection effectiveness.
- To determine whether auditor expertise moderates the relationship between AI adoption and audit outcome.

2. Literature Review

AI has significantly transformed auditing by improving data analysis, the risk identification and detection of anomalies and fraud. AI-based approaches having machine learning and classification models are capable of processing enormous amounts of financial data and recognizing complex patterns that are challenging to detect by using traditional auditing methods (Ngai et al., 2011; Phua et al., 2010; West & Bhattacharya, 2016). Existing studies have confirmed these advantages. Using data from Chinese listed companies (A-shares) spanning 2013 to 2023, demonstrated that advancements in AI have significantly reduced probability and severity of financial fraud (Sun et al., 2025). In the same way, existing research has confirmed that AI-enabled systems enhance capabilities in anomaly detection, classification accuracy and the identification of complex fraud patterns (Özbaltan, 2024).

Research also examined that AI-enabled fraud detection systems outperform than traditional methods, as they were accomplished of analyzing large-scale transaction data and identifying the pattern of complex fraud (Hossain et al., 2025). Furthermore, studies confirmed that the functions of AI-integrated accounting information systems including prevention, detection, data analysis and investigation positively impact the effectiveness of fraud detection (Adeyemi & Ojogbede, 2026).

In Differing manner, the AI effectiveness depends on contextual factors such as data quality, model selection and organizational readiness. This differences with machine learning techniques can produce inconsistent or different results in detecting fraudulent transactions (Sahin and Duman, 2011). It follows that AI adoption alone does not guarantee improved fraud detection; its benefits depend instead on the effectiveness of its implementation and use within the audit context. Study also suggested that the impact of Artificial intelligence on auditing and fraud detection varies depending on the technology employed, with natural language processing identified as a significant factor in certain instances (Qatawneh, 2025).

Auditors showed progressively important role in utilizing information generated by artificial intelligence. The rising complexity of financial fraud schemes has prompted audit firms to adopt machine learning, natural language processing and anomaly detection technologies. While these technologies can increase the accuracy of fraud detection, their benefits are not immediate; auditors must be able to interpret, evaluate and leverage AI-generated results incorporating them into their own professional judgment. Consequently, AI is progressively viewed as a supportive tool rather than a replacement for the auditors. From the above arguments the following hypothesis has been proposed.

H₁: Artificial Intelligence adoption positively influences fraud detection effectiveness.

Research shows that the successful adoption of AI be subject to not only an organizational readiness and regulatory support but also on the auditors

expertise (Azzahra, 2025). Therefore, auditors' professional expertise acting significant moderating role in the relationship between the artificial intelligence adoption and the effectiveness of FDE (fraud detection effectiveness). Expert auditors are more likely to understand AI-generated risk scores, anomaly and analytical results, and to incorporate these elements into their professional judgment.

Conversely, auditors with limited expertise may struggling to interpret and properly utilize information generated by artificial intelligence in to their insight. This argument is support by empirical evidences. A quantitative study of 385 auditors found that technology are closely related to auditor experience and that the interaction between technology and experience is significant; this indicates that the benefits of audit technology are more effectively realized when auditors possess sufficient experience to critically estimate digitalize outputs (Tinyase et al., 2025b).

Research from emerging economies further highlight the significance of auditor expertise. A study in Ghana examined that the implementation of AI had a positive impact on audit outcomes, despite limited resources or circumstances, and that, in some cases, auditor experience could be a strategic asset. These conclusions support investments in technological infrastructure and professional skills development (Tinyase et al., 2025). Likewise, auditors' digital expertise is linked to audit outcomes and that the impact of technology is influenced by the digital maturity level of the client's industry Zhao et al. (2026). These findings indicate that technology, auditor expertise and the organizational environment jointly determine the extent to which AI tools yield beneficial results.

On the one hand, preceding research on the role of expertise has yielded conflicting results. Some studies have shown that experienced auditors are better able to interpret artificial intelligence (AI) outputs, exercise professional judgment and integrate technical information into their audit decisions (Fedyk et al., 2022). On the other side, other studies indicate that the impact of auditor

professionalism may be limited when AI systems are highly automated and standardized (Seethamraju & Hecimovic, 2023). Recent studies suggested that auditors' technical expertise, critical thinking and proficiency with digital tools effect the effectiveness of AI-based analyses in detecting fraud (Suyono et al., 2025). On the contrary, individual characteristics such as innovativeness and resistance to technology have not demonstrated a significant and consistent moderating effect (Nogara, 2024).

Overall, current literature indicates that artificial intelligence (AI) can enhance fraud detection capabilities through improving data analysis, anomaly detection and to identify complex patterns of fraud in auditing engagements. However, the effectiveness of AI adoption varies and often relies heavily on the auditor's expertise. Most of the existing research treated AI adoption and fraud detection as separate topics and few studies integrate AI adoption, fraud detection effectiveness and auditor expertise within a single, comprehensive analytical framework. Research findings on auditor expertise are inconsistent, stressing the need for empirical testing of its moderating effect, particularly in the emerging

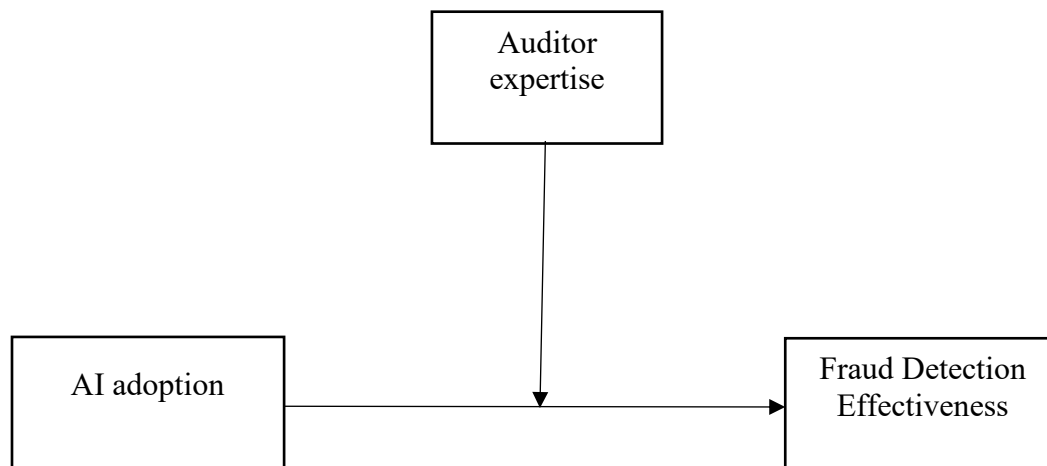
economies. Therefore, this study constructs an integrated model to examine whether AI adoption can improve fraud detection effectiveness and whether auditor expertise strengthen or weak that relationship. From above discussion the following hypothesis is proposed.

H₂: Auditor expertise positively moderates the relationship between Artificial Intelligence adoption and fraud detection effectiveness.

2.1 Conceptual model

On the base of research gaps, the current study proposed conceptual model that linking the use or adoption of AI and fraud detection effectiveness. These factors being moderated by auditor expertise. The model draws upon the TAM, the RBV and Cognitive Fit Theory to explain the theoretical relationships.

The AI adoption is viewed as an independent variable impact the FDE. Auditors' expertise moderates AI adoption and fraud detection effectiveness directly. By simultaneously examining audit outcome, incorporating moderating variables and applying a theory-based approach to a relatively unexplored research area.



3. Research Methodology

3.1 Research Design

This study adopts a positivist philosophical perspective considering technology adoption, expertise and audit outcome as objectively measurable and empirically verifiable factors (Creswell & Creswell, 2018). Demonstration on the TAM, RBV and Cognitive fit Theory, the study used survey data from practicing auditors to formulate and test relevant hypotheses through deductive reasoning. A quantitative cross-sectional survey conducted to examine the relationship between AI adoption, auditor expertise and fraud detection effectiveness. The analysis is based on data collected at specific points in time (Capili, 2021). This model is suitable for SEM analysis, as

this method allows for the evaluation of direct relationships, moderating effects and predictive relationships between variables without requiring longitudinal data (Hair et al., 2022).

3.2 Population and Sampling

The target population encompassed auditors working at accounting firms recognized by the ICAP, including the "Big Four" firms, firms affiliated with international networks and local audit firms. Of 670 questionnaires distributed, 550 were returned and 418 valid responses were retained after excluding incomplete responses. Purposive sampling technique used to select participants with characteristics, knowledge or experiences that align with the research objectives (Etikan et al., 2016).

3.3 Measurement Instrument

Construct	Role	Description	Items	Source of Items
AI Adoption (AIAD)	Independent Variable	Artificial Intelligence adoption refers to the use of Artificial Intelligence tools, AI systems and automated analytics.	6(AIAD1–AIAD6)	Kokina & Davenport (2017); Issa et al. (2016).
Auditor Expertise (AEXP)	Moderating Variable	The level of technical, domain specific and digital competence required for the AI effective use.	6(AEXP1–AEXP6)	Bonner & Lewis (1990); Abdolmohammadi & Wright (1987).
Fraud Detection Effectiveness (FDE)	Dependent Variable	The ability Auditor's to detect anomalies and fraudulent activities by using AI-enabled analytics and anomaly detection systems.	5(FDE1–FDE5)	Bierstaker et al. (2006); Omoteso (2012).

3.4 Data Analysis

Data analyzed by using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4 (Ringle et al., 2022), following Hair et al., (2022) two-stage approach to assessing the measurement model and then the structural model; PLS-SEM was chosen for its suitability to prediction-oriented models involving interaction effects and its robustness to non-normal Likert-scale data. The measurement model was evaluated using indicator loadings (≥ 0.70), Cronbach's alpha, ρ_A and ρ_C (≥ 0.70 , with values above 0.95 flagged as redundant), AVE (≥ 0.50) for convergent validity (Fornell & Larcker, 1981) and

VIF (< 5.0 conventionally, < 3.3 under Kock's, 2015, stricter common-method-bias benchmark) while discriminant validity was confirmed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT < 0.85 ; Henseler et al., 2015). The structural model was assessed through bootstrapping (5,000 resamples, bias-corrected and accelerated, two-tailed, $\alpha = 0.05$), with R^2 interpreted using Hair et al., (2011) benchmarks (weak/moderate/substantial), f^2 interpreted using Cohen's (1988) thresholds (0.02/0.15/0.35), and predictive relevance assessed via PLSpredict-derived Q^2 values (> 0 demonstrating the model outperforms

benchmark; Shmueli et al., 2019); the moderating role of auditor expertise was tested using SmartPLS's two-stage interaction approach, with a significant interaction term ($t > 1.96$, $p < .05$, bootstrap CI excluding zero) taken as evidence of moderation (Henseler and Chin, 2010).

4. Results

4.1 Correlation

Bivariate correlations among the latent constructs, derived from the Fornell-Larcker matrix, indicate that all three constructs are positively and significantly associated. AEXP is moderately-to-strongly correlated with FDE ($r = 0.714$) and moderately correlated with AIAD ($r = 0.585$), while AIAD and FDE show a moderate-to-strong positive correlation ($r = 0.661$). These correlations are all well below the 0.90 threshold that would indicate problematic multicollinearity between constructs (Hair et al., 2019), and they provide preliminary support for the hypothesized relationships prior to structural model testing.

4.2 Measurement Model

4.2.1 Factor Loadings and Collinearity Statistics

All 17 indicators loaded above the recommended 0.70 threshold (range: 0.767–0.917), confirming adequate indicator reliability (Hair et al., 2019). AEXP3 recorded the highest loading (0.892), and AIAD1 the lowest (0.767) – both well within acceptable range.

Indicator-level VIF values ranged from 2.118–4.098. All values fell below the conventional upper limit of 5.0, showing no critical multicollinearity among indicators (Hair et al., 2019). However, applying Kock's (2015) more conservative full-collinearity threshold of 3.3 used specifically to screen for common method bias in single-source, self-reported survey data. The six indicators exceeded this stricter benchmark (AEXP2 = 3.691, AEXP3 = 3.610, AIAD5 = 3.301, AIAD6 = 3.127, FDE2 = 4.098, FDE3 = 3.666). This does not compromise the validity of the model under conventional PLS-SEM guidelines, but it is noted as a methodological limitation given that all constructs measured from a single respondent source at single point in time.

Table 1 FL, CA, CR (rho_a), CR (rho_c), and AVE

Construct(s)	Items	FL	VIF	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
AEXP	AEXP1	0.869	3.240	0.925	0.928	0.942	0.729
	AEXP2	0.878	3.691				
	AEXP3	0.892	3.610				
	AEXP4	0.864	2.791				
	AEXP5	0.804	2.192				
	AEXP6	0.813	2.298				
AIAD	AIAD1	0.767	2.118	0.907	0.917	0.927	0.681
	AIAD2	0.802	2.499				
	AIAD3	0.840	2.929				
	AIAD4	0.826	2.537				
	AIAD5	0.862	3.301				
	AIAD6	0.848	3.127				
FDE	FDE1	0.840	2.370	0.924	0.929	0.943	0.768
	FDE2	0.917	4.098				
	FDE3	0.907	3.666				
	FDE4	0.820	2.208				
	FDE5	0.893	3.266				

4.2.2 Construct Reliability and Convergent Validity

As presented in Table 1, all three constructs exceeded the recommended reliability thresholds; Cronbach's alpha ranged from 0.907 (AIAD) to 0.925 (AEXP), composite reliability (ρ_A) ranged from 0.917 to 0.929 and composite reliability (ρ_C) ranged from 0.927 to 0.943. All comfortably above the 0.70 minimum (Hair et al., 2022) and below the 0.95 upper limit that would suggest item redundancy. AVE values are 0.729 for AEXP, 0.681 for AIAD and 0.768 for FDE, each of them greater than the 0.50 minimum necessary to form convergent validity (Fornell & Larcker, 1981). Overall, these results ratify that the

measurement model validates strong internal consistency and convergent validity of constructs.

4.2.3 Discriminant Validity

Fornell-Larcker criterion

The Discriminant validity confirmed using two complementary criteria such as (i) Fornell-Larcker (ii) HTMT.

Fornell-Larcker criterion,

The square root of the AVE of each construct (AEXP = 0.854, AIAD = 0.825 and FDE = 0.876) are exceeded the aforementioned correlation with all other constructs in the model, thus satisfying the classical requirement that a construct must share more variables with itself (Larcker, 1981).

Table 2 Fornell-Larcker criterion

	AEXP	AIAD	FDE
AEXP	0.854		
AIAD	0.585	0.825	
FDE	0.714	0.661	0.876

Heterotrait -monotrait ratio (HTMT)

This was also confirmed by the HTMT report, which yielded values of 0.621 (AEXP - AIAD), 0.766 (AEXP - FDE), and 0.710 (AIAD - FDE); all these values are lower the traditional threshold of 0.85 (Henseler et al., 2015). This criterion is

considered a more sensitive and reliable test than the Fornell-Larcker test for identifying violations of discriminant validity (Henseler et al., 2015). This concordance between these two criteria provides strong evidence that AEXP, AIAD and FDE are empirically distinct concepts.

Table 3 Heterotrait-monotrait ratio (HTMT) - Matrix

	AEXP	AIAD	FDE
AEXP			
AIAD	0.621		
FDE	0.766	0.710	

4.2.4. Model Predictive Capability

The model explains a significant portion of the variance in fraud detection effectiveness, with an R^2 value of 0.671. According to the criteria of Hair et al. (2011), this level is slightly above the "moderate" threshold (0.50) and close to the "significant" threshold (0.75); this indicates that the implementation of artificial intelligence (AI) and the auditor's expertise together explain 67.1% of the variance in fraud detection effectiveness observed by the auditors.

Analysis of the effect size (f^2) showed that both predictors significantly influenced fraud detection, according to Cohen's (1988) criterion ($f^2 \geq 0.35$): auditor expertise (AEXP) ($f^2 = 0.420$) and artificial intelligence (AIAD) ($f^2 = 0.381$). It is worth noting that the effect size of AEXP is slightly larger than that of AIAD, indicating that auditor expertise plays a slightly more significant role in explaining fraud detection outcomes than the use of AI alone.

The predictive relevance tested by PLSpredict showed a $Q^2_{predict}$ value of 0.636 for Fraud Detection Effectiveness (FDE). This value being significantly greater than zero, the model

demonstrates strong out-of-sample predictive ability and significantly outperforms a naive benchmark model (Shmueli et al., 2019).

Table 2 Model Predictive Capability

Predictor(s)	Outcome	f-square	R-square	$Q^2_{predict}$
AEXP	FDE	0.420	0.671	0.636
AIAD		0.381		

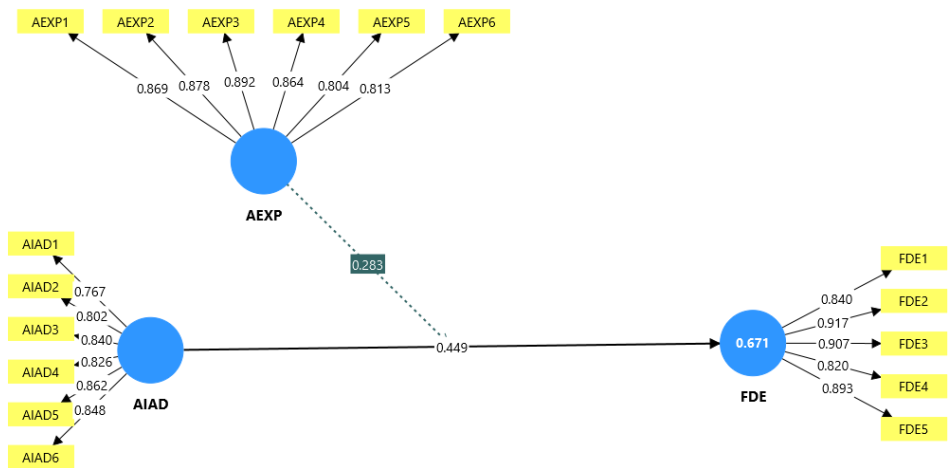


Figure 1 Measurement Model

4.3 Structural Model

4.3.1 Direct Effect

The results of the structural model (Table 5) reveal a positive and statistically significant path (correlation) between AI adoption and fraud detection effectiveness ($\beta = 0.449$, $t = 11.109$, P-Value < 0.001). Since t -value is greater than the critical threshold of 1.96 and P-Value is less than 0.05, hypothesis H2 is confirmed: AI adoption

significantly and positively influences fraud detection effectiveness. This result is consistent with previous empirical studies showing that AI-based anomaly detection and continuous monitoring tools improve auditors' ability to identify patterns of illegal transactions, beyond the limitations of traditional sampling (Izbaltan, 2024; Kumar et al., 2024; Sun et al., 2025).

Table 3 Path Analysis

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-statistics (O/STDEV)	P-values	Status
AIAD -> FDE	0.449	0.450	0.040	11.109	0.000	Significant

4.3.2 Moderation Effect

Table number 6 presents the results of moderated structural model. Auditor expertise showed a strong direct positive effect on fraud detection effectiveness ($\beta = 0.461$, $t = 11.298$, $p < .001$, 95%

CI [0.381, 0.539]), and the AIAD→FDE relationship remained significant within the moderated model ($\beta = 0.449$, $t = 11.109$, $p < .001$, 95% CI [0.369, 0.527]).

The interaction term (AEXP × AIAD → FDE) was statistically significant and positive ($\beta = 0.283$, $t = 8.222$, $p < .001$, 95% CI [0.218, 0.356]). Given that the bootstrapped confidence interval does not

exceed 0, this ratifies a significant moderating effect and H_2 is supported that is “auditor skills significantly moderate the relationship between AI adoption and fraud detection effectiveness”.

Table 4 Moderation

Path(s)	Coefficients	t-statistics (O/STDEV)	P-values	Confidence Interval 95%	
				LLC	ULC
AEXP → FDE	0.461	11.298	0.000	0.381	0.539
AIAD → FDE	0.449	11.109	0.000	0.369	0.527
AEXP × AIAD → FDE	0.283	8.222	0.000	0.218	0.356

The positive sign of the interaction coefficient indicates synergy (reinforcement) rather than compensatory moderation: the positive effect of AI adoption on fraud detection effectiveness is amplified by auditors' expertise, rather than replacing it. Specifically, auditors with higher levels of technical, industry, and digital skills benefit from significantly more effective AI-driven fraud detection than their less expert colleagues. This aligns with the cognitive fit theory (Vessey,

1991), which posits that AI-generated decision-support tools such as anomaly alerts and risk dashboards, only improve performance if the user possesses the cognitive and technical skills to interpret them and act upon them. From a resource management perspective (Barney, 1991; Fedyk, 2022) these valuable resources have intrinsic value and their performance depends on the complementarity of human capital rather than being valuable in isolation.

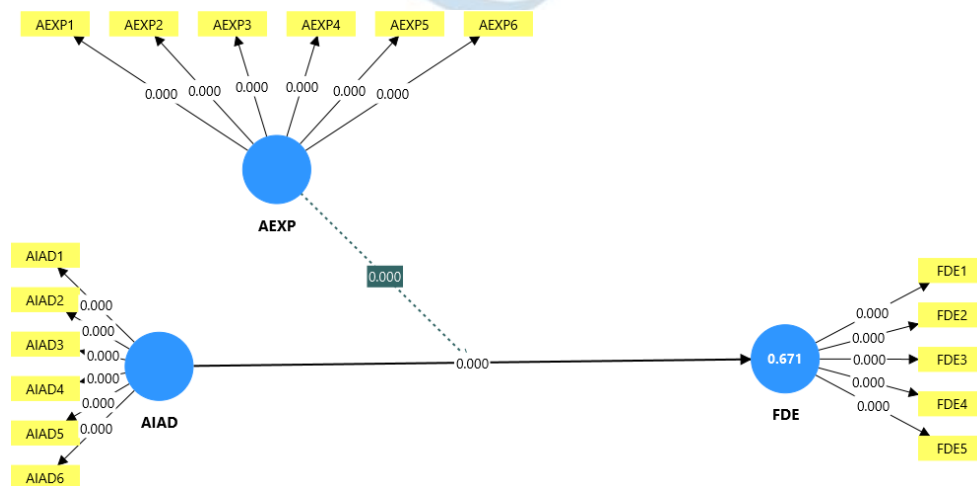


Figure 2 Structural Model

This finding also empirically addresses a tension identified in the literature review: while some researchers have suggested that AI could serve as a compensatory tool to reduce performance gaps by decreasing information overload for less experienced auditors (Bagouzi, 2025; Baharom, 2025). Rozario & Thomas (2021) and Fedyk et al.

(2022) also found that auditors with greater technical and domain expertise derive greater performance benefits from AI-enabled tools.

5.1 Discussion

This study investigates whether the artificial intelligence (AI) adoption enhances fraud

detection effectiveness and whether auditors' expertise moderate the relationship between the two. Results from the structural equation model (PLS-SEM) strongly support both research questions. The AI adoption has a significant positive impact on fraud detection effectiveness ($\beta=0.449$, $t = 11.109$, P-value is less than 0.001; f^2 is 0.381), ratifying H_1 and indicating that Artificial Intelligence (AI) contributes significantly to fraud detection effectiveness.

Auditor expertise similarly has a significant direct influence on the FDE ($\beta = 0.461$, $t = 11.298$, $p < 0.001$; $f^2 = 0.420$). Furthermore, the interaction effect between AI adoption and auditor expertise is significantly positive ($\beta = 0.283$, $t = 8.222$, P-value is less than 0.001; 95% Confidence interval is [0.218, 0.356]), by this means ratifying H_2 . It identifies that auditor expertise improves the advantages resulting from AI adoption rather than replacing AI. This finding supports cognitive fit theory and the resource-based view, suggesting that AI can generate greater value when auditors possess the necessary expertise containing technical, digital and professional competencies to interpret and apply AI-generated information.

The model explains 67.1 percent of the variance in fraud detection performance ($R^2 = 0.671$), and the Q^2 value is 0.636 which shows a high predictive accuracy. The Overall results determine that artificial intelligence adoption increases fraud detection effectiveness with auditor expertise playing an important role.

5.2 Recommendations

- To Consider AI and audit training as complementary investments to maximize the benefits of artificial intelligence (AI).
- To deliver training intensive on interpreting, evaluating and verifying AI generated results.
- To Leverage the guidance or support of experienced auditors to enhance their professional judgment when reviewing transactions flagged by AI.
- Small and medium-sized enterprises can adopt cost-effective, cloud-based AI solutions while

simultaneously investing in necessary staff training.

- Form AI expertise certification pathways for auditors like to current technical certifications recognizing that professional expertise (rather than merely using tools) determines fraud detection.
- Instead of evaluating AI Adoption separately, integrate frameworks for auditor expertise into guidelines and inspection standards for digital auditing.
- Encourage the development of disclosure or governance requirements regarding AI model transparency, as the literature shows that it is more difficult, especially for less experienced auditors, to accurately interpret opaque results in the verification process.
- Incorporating data analytics, machine learning capabilities and the interpretation of AI-generated data into audit curricula and continuous professional development programs that enable new auditors to skillfully use AI tools.
- Conduct AI-enabled fraud detection training to enhance professional skepticism among auditors, and equipping them to identify situations where its results might be misleading or where bias exists.

5.3 Implications

- This study suggests an integrated, empirically validated model that integrates AI adoption, auditing expertise, and fraud detection effectiveness, thus addressing conceptual gaps in the existing literature. By emphasizing synergies rather than compensatory interactions, the model extends cognitive fit theory, the Technology Acceptance Model (TAM) and resource-based theory to audit and technology. This provides empirical support for the conceptualization of auditing expertise as a limiting factor on the value brought by technology, rather than as an independent predictor.
- The key practical point for audit firm leaders is that the use of artificial intelligence (AI) is not a sufficient strategy; this type of technology investment can add value in fraud detection if applied by technically and digitally savvy auditors.

Firms adopting AI without an appropriate talent acquisition strategy may not be able to exploit the full potential of the technology, but firms that integrate them will gain cumulative and mutually reinforcing benefits rather than the sum of their individual gains.

- For regulators and professional bodies, these results highlight the need for a change in the direction of public policy: shifting from an analysis of the extent of AI adoption to a broader consideration of auditor skills and readiness. The certification frameworks, training requirements and digital readiness standards proposed by bodies such as the SECP, the SBP, the ICAP and the ACCA must all take full account of this complementarity in their design stage.

5.4 Limitations

- Study nature: Data collected at a single point in time (Cross-sectional design) permits for the examination of relationships between variables but limits the ability to draw causal conclusions and measure changes over time.
- The perceptual Measure: The effectiveness of fraud detection was evaluated based on auditors' self-reported perceptions rather than objective performance.
- Scope of sample: This study targeted only auditors registered with Institute of Chartered Accountants of Pakistan (ICAP) in Pakistan; therefore, the generalizability of the results to other professionals or different contexts is limited.

5.5 Future research

- Given the significantly stronger moderating role of expertise for fraud detection, future studies could disaggregate auditor expertise into specific sub-dimensions (technical AI literacy versus domain audit judgment) to identify which component of expertise is doing the moderating work.
- Given research the comparative study between Big 4 and Non-big 4 firm will be more appropriate in future research on mixed method (qualitative and quantitative study).

5.6 Conclusion

- The current study examines whether fraud detection effectiveness improves by AI Adoption and whether audit expertise moderates that relationship in audit engagement. Using PLS-SEM to analyze data from a survey conducted among auditors of ICAP registered firms in emerging economy Pakistan. The study ratifies that AI adoption has a positive impact on fraud detection (H1) and auditor expertise significantly and positive moderate the relation between AI adoption and fraud detection effectiveness (H2). The "positive interaction term" reflects an expertise-enhancing effect: AI's benefits in fraud detection increase rather than decrease as auditors expertise increase. The model explains 67.1% of the variance in fraud detection and shows high predictive accuracy in model. The main conclusion is that AI adoption and auditor sophistication are complementary, rather than substitutable in the context of fraud detection. Therefore, audit firms, regulators, and educational institutions in Pakistan and similar emerging markets should view technology investment and human capital development as common goals or common agenda. AI tools can achieve the best results in fraud detection only if auditors have the necessary professional, domain and digital expertise to interpret and apply the data revealed by these tools.

REFERENCE

- Abdol Mohammadi, M., & Wright, A. (1987). An examination of the effects of experience and task complexity on audit judgments. *Accounting Review*, 1-13.
- Adeyemi, T. O., & Ojogbede, A. O. (2026). Artificial intelligence-enabled accounting information systems and fraud detection in Nigeria's financial services sector: The moderating role of natural language processing.
- Alharasis, E. E., & Hu, G. (2026). Artificial intelligence adoption and audit quality in an emerging country: Does auditor experience matter? *EDPACS*

- Anwar, A., & Akeel, M. O. (2026). Integrating artificial intelligence in audit workflow: Opportunities, architecture, and challenges: A systematic review. Preprints.org.
- Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International journal of accounting information systems*, 25, 29-44.
- Azzahra, A. S. (2025). The use of Artificial Intelligence (AI) in Fraud Detection by Government Auditors: A Systematic Literature Review. In *International Conference on Multidisciplinary Studies Integrating Entrepreneurial Strategies and Digital Transformation* (Vol. 1, No. 1, pp. 1-13).
- Bagouzi, K., Abi, K., & Serdouk, F. (2025). The future of auditing: How AI will transform the profession by 2030. *Journal of International Commercial Law and Technology*, 6(1), 370-389.
- Baharom, Z. (2025). The transformative role of artificial intelligence in internal auditing: A critical review. *International Journal for Research and Innovation in Social Science*.
- Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Bierstaker, J. L., Brody, R. G., & Pacini, C. (2006). Accountants' perceptions regarding fraud detection and prevention methods. *Managerial Auditing Journal*, 21(5), 520-535.
- Birhane, A., Steed, R., Ojewale, V., Vecchione, B., & Raji, I. D. (2024). AI auditing: The broken bus on the road to AI accountability. In *2024 IEEE Conference on Secure and Trustworthy Machine Learning (SaTML)* (pp. 612-643). IEEE.
- Bonner, S. E., & Lewis, B. L. (1990). Determinants of auditor expertise. *Journal of accounting research*, 28, 1-20.
- Capili, B. (2021). Overview: Cross-sectional studies. *The American journal of nursing*, 121(10), 59.
- Ceki, B., & Moloi, T. (2025). Technology Adoption Framework for Supreme Audit Institutions within the hybrid TAM and TOE model. *Journal of Risk and Financial Management*, 18(8), 409.
- Celestin, M., & Vanitha, N. (2019). Artificial intelligence in fraud detection: Are traditional auditing methods outdated. In *2nd International Conference on Recent Trends in Arts, Science, Engineering & Technology* (Vol. 3, No. 2, pp. 180-186).
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. routledge.
- Commerford, B. P., Dennis, S. A., Joe, J. R., & Wang, J. (2022). Man versus machine: Complex estimates and auditor reliance on artificial intelligence. SSRN.
- Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.
- Davis, F. D. (1989). Technology acceptance model: TAM. Al-Suqri, MN, Al-Aufi, AS: *Information Seeking Behavior and Technology Adoption*, 205(219).
- Elumilade, O. O., Ogundeji, I. A., Achumie, G. O., Omokhoa, H. E., & Omowole, B. M. (2021). Enhancing fraud detection and forensic auditing through data-driven techniques for financial integrity and security. *Journal of Advanced Education and Sciences*, 1(2), 55-63.
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1-4.
- Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, 27(3), 938-985.

- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- George, M. Z., Alam, M. K., & Hasan, M. T. (2025). Machine learning for fraud detection in digital banking: A systematic literature review.
- Ghafar, I., Perwitasari, W., & Kurnia, R. (2024). The role of artificial intelligence in enhancing global internal audit efficiency: An analysis. *Asian Journal of Logistics Management*, 3(2), 64-89.
- Gu, H., Schreyer, M., Moffitt, K., & Vasarhelyi, M. A. (2024). Artificial intelligence copiloted auditing. *International Journal of Accounting Information Systems*, 54, 100698.
- Hady, A. F., & Mudhaffar, M. A. (2025). Artificial Intelligence Adoption and Audit Quality: A Mediating Model of Performance Expectancy in East Java's Public Accounting Firms. *Journal of Management, Accounting, and Administration*, 2(2), 68-78.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139-152.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24.
- Handoko, B. L., & Liusman, S. (2021). Analysis of external auditor intentions in adopting artificial intelligence as fraud detection with the unified theory of acceptance and use of technology (UTAUT) approach. In *Proceedings of the 2021 12th International Conference on E-business, Management and Economics* (pp. 96-103). ACM.
- Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural equation modeling*, 17(1), 82-109.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43(1), 115-135.
- Hossain, M. Z., Alam, M. K., & Hasan, M. T. (2025). Machine learning for fraud detection in digital banking: A systematic literature review. *arXiv preprint*.
- Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *Journal of emerging technologies in accounting*, 13(2), 1-20.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec)*, 11(4), 1-10.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1-10.
- Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*, 14(1), 115-122.
- Kumar, R., Verma, H., Upadhyaya, R., Malik, A., Kumar, L., & Singh, D. B. (2024). AI-powered fraud detection in financial transactions: A machine learning approach. *Journal of Information Systems Engineering and Management*, 9(4s).
- Kumar, R., Verma, H., Upadhyaya, R., Malik, A., Kumar, L., & Singh, D. B. (2024). AI-powered fraud detection in financial transactions: A machine learning approach. *Journal of Information Systems Engineering and Management*, 9(4s).

- Li, Y., & Goel, S. (2024). Artificial intelligence auditability and auditor readiness for auditing AI systems. *International Journal of Accounting Information Systems*.
- Maryani, N., Muchlish, M., Mulyadi, R., & Solehah, N. (2026). Blockchain-Based Audit Trails: Improving Transparency and Fraud Detection in Digital Accounting Systems. *International Journal of Advanced Computer Science & Applications*, 17(1), 648.
- Naseer, K., & Ahmed, H. N. (2025). Effectiveness and reliability of artificial intelligence in fraud detection: A mixed-method study on financial audit. *Journal of Management and Informatics*, 4(1), 706-722.
- Ngai, E. W. T., 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.
- Nugraha, G. C. H. (2024). Perception of artificial intelligence adoption on audit quality. *ABIS: Accounting and Business Information Systems Journal*, 12(1), 835-844.
- Omoteso, K. (2012). The application of artificial intelligence in auditing: Looking back to the future. *Expert Systems with Applications*, 39(9), 8490-8495.
- Özbaltan, N. (2024). Applying machine learning to audit data: Enhancing fraud detection, risk assessment and audit efficiency. *EDPACS*, 69(9), 70-86.
- Phua, C., Lee, V., Smith, K., & Gayler, R. (2010). A comprehensive survey of data mining-based fraud detection research.
- Qatawneh, A. M. (2025). The role of artificial intelligence in auditing and fraud detection in accounting information systems: Moderating role of natural language processing. *International Journal of Organizational Analysis*, 33(6), 1391-1409.
- Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. SmartPLS GmbH.
- Rozario, A. M., & Vasarhelyi, M. A. (2018). Auditing with smart machines. *The CPA Journal*, 88(6), 24-29.
- Sahin, Y., & Duman, E. (2011). Detecting credit card fraud by decision trees and support vector machines. *Expert Systems with Applications*, 38(10), 13056-13061.
- Salijeni, G., Samsonova-Taddei, A., & Turley, S. (2021). Understanding how big data technologies reconfigure the nature and organization of financial statement audits: A sociomaterial analysis. *European Accounting Review*, 30(3), 531-555.
- Schreyer, M., Gu, H., Moffitt, K., & Vasarhelyi, M. A. (2024). Artificial intelligence agentic auditing. SSRN Working Paper.
- Seethamraju, R., & Hecimovic, A. (2023). Adoption of artificial intelligence in auditing: An exploratory study. *Australian Journal of Management*, 48(4), 780-800.
- Shivram, V. (2024). Auditing with AI: A theoretical framework for applying machine learning across the internal audit lifecycle. *International Journal of Accounting Information Systems*.
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322-2347.
- Sun, G., Ling, Z., Li, Y., & Xie, C. (2025). Artificial intelligence and financial fraud. *Pacific-Basin Finance Journal*, 93, 102830.
- Suyono, W. P., Puspa, E. S., Anugrah, S., & Firnanda, R. (2025). Redefining fraud detection: The synergy between auditor competency and AI-powered audit analytics. *Journal of Artificial Intelligence and Digital Business (RIGGS)*, 4(3), 953-960.

Talukder, M. A., Khalid, M., & Uddin, M. A. (2024). An integrated multistage ensemble machine learning model for fraudulent transaction detection. *Journal of Big Data*, 11, 168.

Tinyase, K. O., Ocansey, E. O. N. D., & Asamoah, F. O. (2025a). Moderating effect of auditor experience in the interplay of technology, motivation, time pressure, and audit quality. *African Journal of Accounting and Financial Research*, 8(3), 39–65.

Tinyase, K. O., Ocansey, E. O. N. D., & Asamoah, F. O. (2025b). Technology and audit quality: Moderating role of auditor experience. *Journal of Accounting*, 7(2), 30–46.

Tiron-Tudor, A., & Deliu, D. (2022). Reflections on the human-algorithm complex duality perspectives in the auditing process. *Qualitative Research in Accounting & Management*, 19(3), 255–285.

Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. *Accounting Horizons*, 29(2), 381–396.

Vessey, I. (1991). Cognitive fit: A theory-based analysis of the graphs versus tables literature. *Decision Sciences*, 22(2), 219–240.

Wassie, F. A., & Lakatos, L. P. (2024). Artificial intelligence and the future of the internal audit function. *Humanities and Social Sciences Communications*, 11, 386.

West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, 57, 47–66.

Zhao, T., Duan, W., & Mao, Y. (2026). Auditors' digital expertise and audit quality: Empirical evidence based on China's A-share listed companies. *Emerging Markets Finance and Trade*, 62(2), 420–438.