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A Structural Analytical Framework for Technology-Driven Fraud Detection and Audit Outcomes

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ABSTRACT. This paper develops a structural analytical model to examine the relationships between technology-related capabilities and audit outcomes through an intermediate analytical mechanism. Within a quantitative structural analysis framework, the study investigates the effects of artificial intelligence adoption, data analytics capability, and auditor IT competence on fraud detection effectiveness, and examines the mediating role of fraud detection effectiveness in determining audit quality. The empirical model is estimated using survey data from 298 external auditors in Vietnam and analysed via Partial Least Squares–based structural equation modelling. The results show that artificial intelligence adoption, data analytics capability, and auditor IT competence have positive and statistically significant structural effects on fraud detection effectiveness, with artificial intelligence adoption exhibiting the largest standardized coefficient. In addition, fraud detection effectiveness exerts a strong positive effect on audit quality and fully mediates the relationships between technology-related capabilities and audit outcomes. The proposed structural framework provides an applied analytical interpretation of how technology-driven mechanisms influence audit performance and offers implications for the design of technology-enabled audit systems in emerging markets.

1. Introduction

Financial fraud continues to undermine the credibility of financial reporting and the reliability of audit outcomes, particularly in increasingly complex and digitalized business environments. As organizations process larger volumes of transactional data through advanced information systems, traditional audit approaches that rely heavily on manual procedures and limited sampling face growing challenges in identifying sophisticated fraud schemes [1], [2].

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Strengthening fraud detection effectiveness has therefore become a critical priority for auditors and regulators seeking to safeguard audit quality and stakeholder confidence.

In recent years, auditing practices have progressively incorporated technological tools to enhance auditors' ability to identify and assess fraud risks. Prior research suggests that audit quality is increasingly shaped by auditors' effectiveness in detecting fraud rather than solely by formal compliance with auditing standards [3], [4]. Within this context, fraud detection effectiveness plays a central role by reducing detection risk and improving the reliability of audit opinions [2].

Existing studies identify several technological and human-capital factors that are particularly relevant to fraud detection in modern audits. Artificial intelligence (AI) has been widely discussed for its capacity to support anomaly detection and data-driven judgment in complex audit environments [5], [6], [7]. At the same time, data analytics has become an essential component of contemporary auditing, enabling auditors to analyse large datasets more comprehensively than traditional sampling-based approaches [8], [9]. In addition, auditors' information technology (IT) competence is recognized as a key enabler that determines whether advanced tools such as computer-assisted audit techniques can be effectively applied in practice [10], [11].

Despite this growing body of research, important gaps remain. First, prior studies tend to examine AI adoption, data analytics, and auditor IT competence separately, offering limited insight into how these factors jointly shape fraud detection effectiveness. Second, while technology has been linked to audit quality, empirical evidence explaining how technological resources translate into improved audit outcomes-particularly through fraud detection effectiveness as an intervening mechanism - remains scarce [12]. Third, most existing evidence is drawn from developed economies, leaving emerging markets underrepresented, despite their distinct institutional and technological constraints [13], [14].

To address these gaps, this study develops a structural analytical framework to examine how technology-enabled capabilities influence audit quality through fraud detection effectiveness in Vietnam, an emerging economy where audit technology adoption is increasing but remains uneven. Specifically, the study analyses the structural relationships between artificial intelligence adoption, data analytics capability, auditor IT competence, and fraud detection effectiveness, and subsequently examines the role of fraud detection effectiveness as a mediating mechanism affecting audit quality. By conceptualising fraud detection effectiveness as an analytical capability linking technological and human-capital resources to audit outcomes, this study provides a structured quantitative explanation of how technology enhances audit quality.

This study contributes to the auditing literature in three ways. First, it integrates technological and human-capital factors within a single empirical framework. Second, it

empirically demonstrates the mediating role of fraud detection effectiveness in the relationship between technology-related resources and audit quality. Third, it extends existing research by providing evidence from an emerging market context.

2. Theoretical background

2.1. Resource-Based View (RBV)

The Resource-Based View (RBV) posits that organizational performance and competitive advantage depend on the possession and deployment of valuable, rare, inimitable, and non-substitutable resources [15], [16]. In the auditing context, technological resources-such as AI adoption (AIA), data analytics capability (DAC), and auditor IT competence (ITC)-serve as strategic assets that enhance auditors' ability to perform their work more effectively.

From an RBV perspective, the value of these resources lies not merely in their existence, but in how they are combined and applied to develop organizational capabilities that support superior performance [15], [16]. In this study, fraud detection effectiveness (FDE) is conceptualized as such a capability through which technological and human-capital resources are translated into audit outcomes. When auditors possess strong IT competence, leverage advanced data analytics, and adopt AI tools, they are better equipped to identify anomalies, detect fraudulent patterns, and assess audit risks more accurately.

Accordingly, RBV provides a robust theoretical foundation for explaining the relationships between AIA, DAC, ITC, and FDE. These technological and human-capital resources form the basis upon which auditors develop the capability to detect fraud effectively, thereby contributing to higher audit quality.

2.2. Audit risk model (ARM)

The Audit Risk Model (ARM), as articulated in international auditing standards (e.g., ISA 200, ISA 315), conceptualizes audit quality as a function of inherent risk, control risk, and detection risk [1]. Within this framework, fraud detection effectiveness (FDE) is directly associated with detection risk, which reflects the likelihood that auditors fail to identify material misstatements or fraudulent activities during the audit process.

Higher fraud detection effectiveness reduces detection risk and, consequently, increases the likelihood that auditors issue accurate and reliable audit opinions. This perspective is consistent with [2], who emphasizes that audit quality is closely linked to auditors' ability to manage detection risk effectively and to exercise sound professional judgment in increasingly complex and technology-driven audit environments.

Accordingly, ARM provides a strong theoretical foundation for explaining the relationship between fraud detection effectiveness and audit quality. By lowering detection risk, effective fraud detection strengthens the audit process and enhances the credibility of audit

outcomes, supporting the assertion that fraud detection effectiveness is a key determinant of audit quality.

2.3. Agency theory

Agency Theory explains the contractual relationship between principals (shareholders) and agents (managers), emphasizing the problems that arise from information asymmetry and conflicting interests [17]. Managers may conceal information or engage in opportunistic behaviour, including financial fraud, which increases agency costs. External audits help mitigate these risks by providing independent assurance [4].

Within this framework, fraud detection effectiveness (FDE) is essential for reducing agency problems. When auditors are effective in identifying fraud, the level of information asymmetry declines, managerial misconduct is constrained, and the credibility of financial reports improves. As a result, stakeholders obtain more reliable information, which directly contributes to enhanced audit quality (AQ).

Agency Theory therefore reinforces the central role of FDE in improving AQ by demonstrating how effective fraud detection reduces agency conflicts and strengthens the accountability of management.

2.4. Summary of theoretical integration

The integration of these three theories provides a comprehensive theoretical foundation for the proposed research model. Resource-Based View explains how AI adoption, data analytics capability, and auditor IT competence constitute strategic technological and human-capital resources that give rise to fraud detection effectiveness as a critical auditing capability. The Audit Risk Model clarifies how fraud detection effectiveness reduces detection risk and, in turn, enhances audit quality. Agency Theory highlights the broader governance role of fraud detection effectiveness in mitigating information asymmetry and agency costs, thereby further contributing to higher audit quality.

Taken together, these theoretical perspectives support the conceptual logic and causal structure of the research framework by explaining how technological resources are transformed into fraud detection capabilities and how such capabilities ultimately improve audit quality within the governance role of auditing.

3. Literature review and hypotheses development

3.1. AI adoption and fraud detection effectiveness

Artificial intelligence (AI) has increasingly been recognized as a transformative tool in auditing due to its capacity to process large volumes of data, identify complex patterns, and support auditors' professional judgment in highly information-intensive environments. Unlike traditional rule-based audit procedures, AI techniques such as machine learning enable auditors

to detect subtle anomalies and irregular transaction patterns that may signal fraudulent behavior, thereby enhancing fraud detection effectiveness [6], [7].

Prior studies suggest that AI adoption enhances auditors' ability to analyse structured and unstructured data, automate repetitive detection tasks, and continuously learn from historical fraud cases. These capabilities are particularly relevant in fraud detection contexts, where fraudulent schemes are adaptive and often designed to evade conventional audit tests. By expanding auditors' analytical reach and enabling more comprehensive data examination, AI-supported audit tools contribute to more effective identification of fraud-related red flags [18], [19].

Importantly, the effectiveness of AI in fraud detection depends not only on technical sophistication but also on how AI tools are integrated into audit workflows. [20] emphasize that AI should be viewed as a complementary tool that enhances, rather than replaces, auditors' professional judgment. When appropriately implemented, AI supports auditors' decision-making processes and strengthens their ability to identify fraud, rather than fully automating fraud detection tasks.

Recent research also highlights challenges related to trust and transparency in AI-enabled auditing. Concerns regarding the "black-box" nature of certain AI models may limit auditors' reliance on AI outputs, potentially constraining their impact on fraud detection effectiveness [21]. The development of explainable artificial intelligence (XAI) has therefore been proposed as a means to improve transparency and enhance auditors' confidence in AI-driven decisions [22].

Overall, the literature indicates a positive relationship between AI adoption and fraud detection effectiveness. By enabling advanced pattern recognition, continuous data analysis, and enhanced auditor judgment, AI adoption is expected to strengthen auditors' ability to detect fraudulent activities. Accordingly, this study proposes the following hypothesis:

H1: AI adoption positively influences fraud detection effectiveness.

3.2. Data analytics capability and fraud detection effectiveness

Data analytics capability has become an essential component of modern auditing as audit firms increasingly adopt data-driven approaches to identify and assess fraud risks. Unlike traditional audit methods that rely heavily on sampling, data analytics enables auditors to examine entire populations of transactions, detect anomalies, and identify unusual patterns that may signal fraudulent activities. Prior studies indicate that such comprehensive data examination significantly enhances auditors' ability to uncover fraud-related irregularities that might otherwise remain undetected [8], [9], [23].

Beyond the mere use of analytical tools, data analytics capability reflects auditors' ability to effectively process, analyse, and interpret large volumes of audit-relevant data. Techniques such as statistical analysis, visualization, and pattern recognition allow auditors to identify

outliers and trends associated with fraudulent behaviour, thereby improving the accuracy and consistency of fraud detection procedures [24]. By reducing reliance on judgmental sampling, data analytics supports more systematic and evidence-based fraud detection.

Furthermore, prior research suggests that audit data analytics facilitates more proactive and continuous audit approaches by enabling earlier identification of fraud risks and ongoing monitoring of transactional data [8], [25]. However, the effectiveness of analytics-based fraud detection depends critically on the quality of the underlying data. High-quality and reliable data are essential to ensure that analytical outputs meaningfully support auditors' fraud detection judgments [26].

Overall, the literature indicates that data analytics capability enhances fraud detection effectiveness by enabling comprehensive data analysis, advanced anomaly identification, and more proactive fraud risk assessment. Accordingly, this study proposes the following hypothesis:
H2: Data analytics capability positively influences fraud detection effectiveness.

3.3. Auditor IT competence and fraud detection effectiveness

Auditor IT competence has become increasingly important as auditing environments grow more complex and data-intensive. As audit firms adopt advanced technologies and computerized systems, auditors are expected not only to understand audit standards but also to possess sufficient IT-related knowledge and skills to effectively apply technology in fraud detection tasks. Prior research suggests that auditors with stronger IT competence are better equipped to utilize computer-assisted audit techniques (CAATs) and analytical tools to identify irregularities and potential fraud [10], [11].

Auditor IT competence refers to the ability to understand, operate, and interpret outputs from audit-related information systems and technological tools. Such competence enables auditors to design more effective audit procedures, analyse large volumes of electronic data, and recognize abnormal patterns that may indicate fraudulent activities. By enhancing auditors' ability to interact with audit technologies, IT competence reduces the likelihood that fraud-related signals embedded in complex datasets remain undetected [12], [27].

Empirical evidence further indicates that IT-competent auditors are more likely to integrate technology into their audit workflows and rely on data-driven evidence when assessing fraud risks. Siew et al. (2020)[28] find that auditors with higher levels of IT knowledge demonstrate greater adoption and more effective use of CAATs, which in turn strengthens fraud detection efforts. In contrast, limited IT competence may constrain auditors' ability to fully exploit available technological tools, thereby weakening the effectiveness of fraud detection procedures.

Overall, the literature suggests that auditor IT competence plays a critical enabling role in fraud detection. By enhancing auditors' ability to apply and interpret technology-based audit

tools, IT competence supports more thorough data analysis and improves the identification of fraud-related anomalies. Accordingly, this study proposes the following hypothesis:

H3: Auditor IT competence positively influences fraud detection effectiveness.

3.4. Fraud detection effectiveness and audit quality

Fraud detection effectiveness is widely regarded as a critical determinant of audit quality, as the primary objective of an audit is to provide reasonable assurance that financial statements are free from material misstatement due to error or fraud. Within the audit risk framework, effective fraud detection reduces detection risk, thereby increasing the likelihood that auditors identify material misstatements and issue appropriate audit opinions [1], [2].

Prior research suggests that auditors who are more effective in detecting fraud are better able to assess audit risk, focus audit efforts on high-risk areas, and obtain sufficient and appropriate audit evidence. [10] argue that enhanced fraud detection capabilities strengthen the reliability of audit outcomes by improving auditors' ability to uncover irregularities that might otherwise remain undetected. Similarly,[12] highlight that proactive fraud detection enhances the overall quality of the audit process by supporting more thorough investigation and professional judgment.

From a governance perspective, effective fraud detection also contributes to higher audit quality by reducing information asymmetry between managers and stakeholders. When auditors successfully identify and respond to fraudulent activities, the credibility of financial reporting improves, reinforcing stakeholders' confidence in audited financial statements [4]. More recent evidence further supports the view that stronger fraud detection effectiveness is associated with higher audit quality through improved transparency and reliability of audit outcomes [29].

Overall, the literature indicates a positive relationship between fraud detection effectiveness and audit quality. By reducing detection risk, strengthening audit procedures, and enhancing the credibility of financial reporting, effective fraud detection is expected to improve audit quality. Accordingly, this study proposes the following hypothesis:

H4: Fraud detection effectiveness positively influences audit quality.

Taken together, these hypotheses imply that fraud detection effectiveness serves as a mediating mechanism through which technological and human-capital resources influence audit quality.

Accordingly, this study examines the impact of AI adoption (AIA), data analytics capability (DAC), and auditor IT competence (ITC) on fraud detection effectiveness (FDE), and subsequently investigates the effect of fraud detection effectiveness on audit quality (AQ). The theoretical research model is presented in Figure 1.

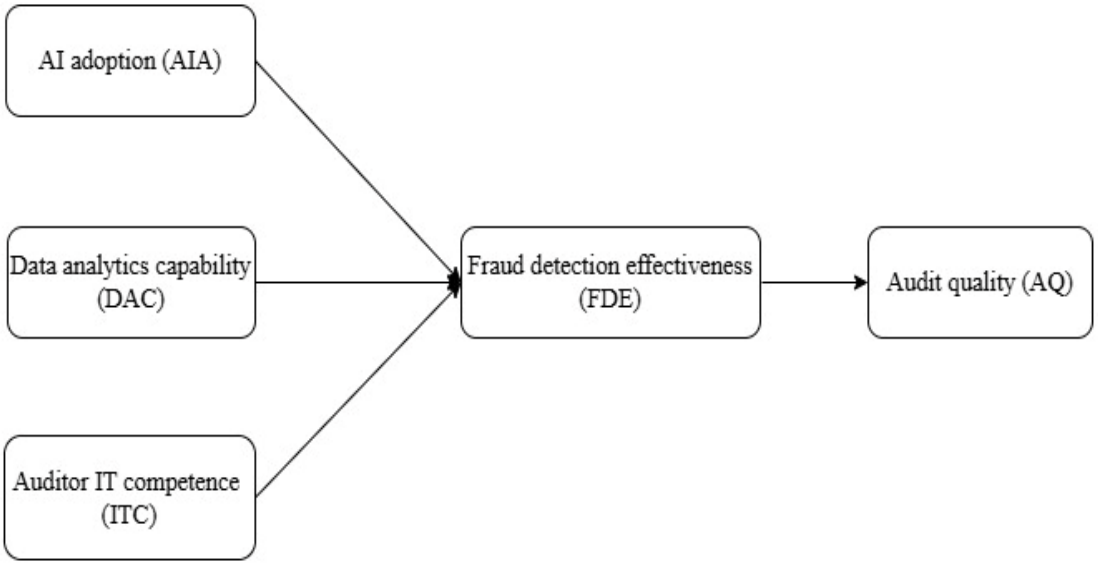

Figure 1. Research model

4. Methods

4.1 Research design

This study adopts a quantitative, cross-sectional survey design to examine the proposed structural equation model (SEM). The model includes three independent variables - AI adoption (AI), data analytics capability (DAC), and auditor IT competence (ITC) - one mediating variable, fraud detection effectiveness (FDE), and one dependent variable, audit quality (AQ). The relationships are tested using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 3, which is widely used for testing complex models in the context of management and auditing research [30].

4.2 Sample and data collection

The target population consists of external auditors from both Big 4 and non-Big 4 audit firms in Vietnam. Data were collected through an online questionnaire distributed via email and professional networking groups between March and May 2025. Consistent with PLS-SEM guidelines, the obtained sample size exceeds the minimum requirements for estimating complex structural models [30]. After screening for completeness and consistency, a total of 298 valid responses were retained for analysis. To ensure relevant expertise, respondents were required to have at least two years of audit experience and prior involvement in fraud risk assessment activities.

4.3 Measurement development

All constructs were measured using multiple-item scales adapted from prior validated studies, rated on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). AI adoption items were adapted from [7] and [6], who explored AI adoption in auditing

contexts and its impact on audit processes. DAC items were based on [8] and [9], who highlighted the importance of data analytics in enhancing audit quality and fraud detection. ITC items were adapted from [11], whose research examined the significance of IT skills for auditors in effectively using audit software. FDE items were adapted from [12], who studied the impact of fraud detection capabilities on audit outcomes. AQ items were based on [3], who identified the key factors that determine audit quality. The questionnaire was translated into Vietnamese and back-translated to ensure semantic equivalence, following standard procedures for ensuring the validity of survey instruments across languages [31]. In the Vietnamese context, [14] found that auditors increasingly recognize the importance of audit technology in practice, providing additional support for the measurement design.

4.4. Data analysis procedure

Data analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 3, following established guidelines [30]. A two-step approach was employed, beginning with the assessment of the measurement model, which involved evaluating indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. This sequential evaluation is consistent with widely accepted PLS-SEM procedures [30] and aligns with recent conceptual discussions on validity in structural equation modelling research [32], which distinguish between construct-related validity (e.g., content, convergent, and discriminant validity) and relationship-related validity (e.g., nomological and predictive validity).

The structural model was then evaluated by examining path coefficients, t-values, p-values, coefficients of determination (R^2), and effect sizes. Bootstrapping with 5,000 subsamples was applied to assess the statistical significance of the hypothesized relationships. PLS-SEM is particularly suitable for studies involving complex structural models with multiple relationships and moderate sample sizes, such as the present research [30].

5. Results and discussion

5.1 Measurement model assessment

To analyze the structural model using SmartPLS, [30] suggest evaluating the measurement model based on construct reliability, convergent validity, and discriminant validity. Construct reliability was evaluated using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Convergent validity was assessed through factor loadings and AVE, while discriminant validity was evaluated using the Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait (HTMT) ratio. As indicated in Table 1, all Cronbach's Alpha and Composite Reliability (CR) values exceeded the recommended threshold of 0.70, signifying satisfactory internal consistency reliability [30]. The Average Variance

Extracted (AVE) values for all constructs were above the 0.50 threshold, further validating the convergent validity of the model.

Table 1. Construct reliability and validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AIA	0.948	0.963	0.865
DAC	0.946	0.961	0.861
ITC	0.929	0.955	0.875
FDE	0.955	0.967	0.881
AQ	0.937	0.955	0.840

In table 2, the square root of AVE for each construct (diagonal values) was greater than its highest correlation with any other construct, thus satisfying the Fornell–Larcker criterion for discriminant validity [33].

Table 2. Fornell–Larcker criterion

Construct	AIA	DAC	ITC	FDE	AQ
AIA	**0.930**				
DAC	0.476	**0.928**			
ITC	0.370	0.366	**0.935**		
FDE	0.717	0.655	0.643	**0.938**	
AQ	0.573	0.464	0.508	0.741	**0.917**

Finally, the Heterotrait-Monotrait (HTMT) ratio presented in Table 3 was used to further assess discriminant validity. All HTMT values were below the conservative threshold of 0.85 [34], confirming discriminant validity.

Table 3. Heterotrait–Monotrait (HTMT) ratio

Construct	AIA	DAC	ITC	FDE	AQ
AIA	-				
DAC	0.502	-			
ITC	0.394	0.391	-		
FDE	0.753	0.689	0.683	-	
AQ	0.608	0.492	0.544	0.783	-

5.2 Structural model assessment

Before evaluating the hypothesized relationships, collinearity among the predictor constructs was examined. The collinearity diagnostics indicated no multicollinearity issues, as all inner variance inflation factor (VIF) values were well below the recommended threshold of 5, suggesting that collinearity is not a concern in the structural model [30].

Subsequently, the structural relationships were assessed using the bootstrapping procedure with 5,000 subsamples. Table 4 reports the path coefficients, standard deviations, t-statistics, and p-values for the hypothesized relationships. The results indicate that all direct paths are positive and statistically significant at the 1% level. Specifically, AI adoption, data analytics capability, and auditor IT competence exert significant positive effects on fraud detection effectiveness, which in turn has a strong positive impact on audit quality. These findings provide empirical support for all proposed hypotheses.

Table 4. Path coefficients and hypothesis testing

Hypothesis	Path	Original Sample (β)	Standard Deviation	T Statistics	P Values	Conclusion
H1	AIA → FDE	0.430	0.036	12.087	0.000	Significant
H2	DAC → FDE	0.315	0.032	9.902	0.000	Significant
H3	ITC → FDE	0.368	0.031	12.001	0.000	Significant
H4	FDE → AQ	0.741	0.027	27.331	0.000	Significant

To further examine the mediating role of fraud detection effectiveness, the specific indirect effects were assessed using the bootstrapping procedure with 5,000 subsamples. Table 5 reports the indirect effects of AI adoption, data analytics capability, and auditor IT competence on audit quality through fraud detection effectiveness. The results indicate that all indirect effects are positive and statistically significant at the 1% level, providing strong empirical support for the mediating role of fraud detection effectiveness. Given the absence of direct paths from the technological factors to audit quality, these findings confirm that fraud detection effectiveness fully mediates the relationships between technological and human-capital resources and audit quality.

Table 5. Specific indirect effects and mediation analysis

Mediation path	Indirect effect (β)	Standard deviation	T statistics	P values	Mediation type
AIA → FDE → AQ	0.319	0.029	10.900	0.000	Full
DAC → FDE → AQ	0.234	0.024	9.825	0.000	Full
ITC → FDE → AQ	0.273	0.026	10.572	0.000	Full

Table 6 presents the coefficients of determination (R^2 and adjusted R^2) for the endogenous constructs. The results show that the model explains 75.2% of the variance in fraud detection effectiveness and 54.9% of the variance in audit quality, indicating substantial and moderate explanatory power, respectively, according to the criteria suggested by [30]. This demonstrates that the proposed predictors collectively provide a strong explanation of fraud detection effectiveness and a meaningful explanation of audit quality.

Table 6. R^2 values of endogenous constructs

Endogenous construct	R^2	Adjusted R^2
FDE	0.752	0.749
AQ	0.549	0.547

To assess the relative contribution of each exogenous construct, effect sizes (f^2) were examined and are reported in Table 7. The results reveal that AI adoption and auditor IT competence have large effects on fraud detection effectiveness, while data analytics capability exhibits a medium effect. Moreover, fraud detection effectiveness shows a very large effect on audit quality, underscoring its central role as a key mechanism through which technological factors enhance audit quality.

Table 7. Effect size (f^2) for each path

Relationship	f^2	Effect size
AIA → FDE	0.544	Large
DAC → FDE	0.293	Medium
ITC → FDE	0.446	Large
FDE → AQ	1.216	Large

To further support these findings, Figure 2 illustrates the estimated structural model, including the standardized path coefficients and the explained variance (R^2) for the endogenous constructs, providing a comprehensive overview of the model's explanatory power and structural relationships.

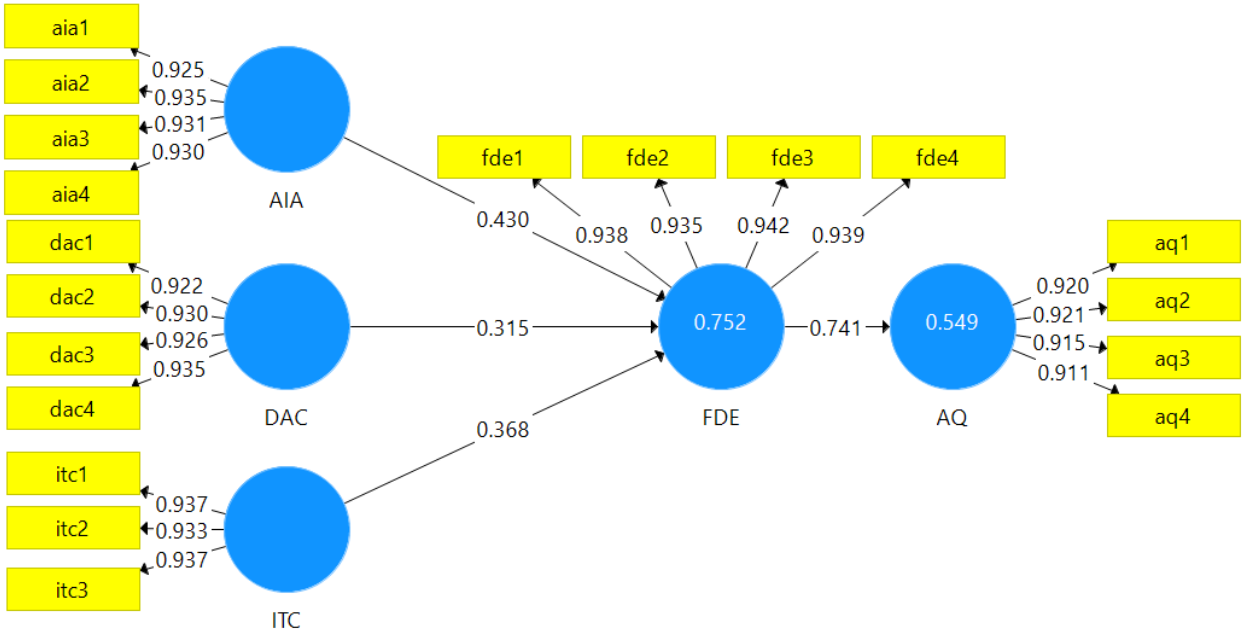

Figure 2. Structural model results

5.3. Model fit and predictive relevance

Model fit was evaluated using several global fit indices to provide additional support for the adequacy of the estimated model. The standardized root means square residual (SRMR) value of 0.030 is well below the recommended threshold of 0.08, indicating a good model fit. In addition, the discrepancy measures d_ULS (0.171) and d_G (0.200) fall within acceptable ranges, further supporting model adequacy. The normed fit index (NFI = 0.942) is close to the ideal value of 1, suggesting a good representation of the observed covariance structure. Although the chi-square statistic ($\chi^2 = 358.968$) is significant, this result is expected in models with relatively large sample sizes and does not detract from the overall assessment of model fit.

Predictive relevance was assessed using the Stone–Geisser Q^2 criterion based on the cross-validated redundancy approach, as reported in Table 8. According to Hair et al. (2019)[30], Q^2 values greater than zero indicate that a model has predictive relevance for its endogenous constructs. In this study, the Q^2 values for fraud detection effectiveness (FDE = 0.655) and audit quality (AQ = 0.456) are well above zero, indicating strong predictive relevance. These results demonstrate that the structural model has substantial capability to predict the endogenous constructs, thereby supporting the robustness of the proposed research framework.

Table 8. Predictive relevance (Q^2 values)

Construct	Q^2	Predictive relevance
FDE	0.655	Yes
AQ	0.456	Yes

5.4 Discussion

This section discusses the empirical findings in light of the proposed theoretical framework and prior literature. Using PLS-SEM, the study examines how AI adoption, data analytics capability, and auditor IT competence influence fraud detection effectiveness, and how fraud detection effectiveness subsequently affects audit quality. Overall, the results support the hypothesized relationships and provide empirical evidence on the mechanisms through which technological and human-capital resources enhance audit quality in an emerging market context.

5.4.1. The impact of AI adoption on fraud detection effectiveness

The results indicate that AI adoption has a positive and statistically significant effect on fraud detection effectiveness ($\beta = 0.430$, $p < 0.001$). Among the three technological predictors, AI adoption exhibits the largest standardized path coefficient, highlighting its important role in strengthening auditors' ability to detect fraud. This finding supports prior research suggesting that AI technologies, such as machine learning and deep learning, enable auditors to analyse large datasets, identify complex patterns, and recognize anomalies that may signal fraudulent behaviour [35], [36], [37]. This finding also aligns with recent data science–oriented research

suggesting that intelligent audit systems enhance pattern recognition and anomaly detection in complex audit settings [38].

At the same time, the effectiveness of AI adoption should be interpreted within the broader implementation context. In Vietnam, AI adoption in auditing is still evolving and may be constrained by factors such as implementation costs, infrastructure limitations, and concerns regarding model transparency and explainability. These contextual factors do not negate the statistical significance of AI's impact, but rather suggest that the realized benefits of AI depend on how effectively it is implemented and integrated into audit processes [21]. Recent developments in explainable artificial intelligence (XAI) have been proposed as a means to address transparency concerns and enhance auditors' trust in AI-generated outputs, thereby strengthening AI's contribution to fraud detection effectiveness [22].

Consistent with [20], the findings reinforce the view that AI should be regarded as a complementary tool that enhances auditors' professional judgment rather than replacing human auditors. When appropriately deployed, AI augments auditors' analytical capabilities and supports more effective fraud detection without undermining the central role of professional scepticism.

5.4.2. The impact of data analytics capability on fraud detection effectiveness

Data analytics capability is also found to have a positive and statistically significant effect on fraud detection effectiveness ($\beta = 0.315$, $p < 0.001$). Although its standardized effect is smaller than that of AI adoption and auditor IT competence, data analytics remains a substantively important determinant of fraud detection effectiveness. This result aligns with prior studies emphasizing that analytics-driven audits enable more comprehensive data examination and more systematic identification of fraud-related anomalies [8], [24].

By allowing auditors to analyse entire populations of transactions rather than relying solely on sampling techniques, data analytics enhances the accuracy and consistency of fraud detection procedures. Analytical approaches such as anomaly detection, trend analysis, and pattern recognition support the identification of irregular transaction patterns that may not be observable through traditional audit methods [8], [24]. Moreover, data-driven auditing has been shown to support more proactive fraud risk assessment by enabling predictive analysis and continuous monitoring of high-risk transactions [25].

In the Vietnamese auditing context, data analytics tools may represent a relatively practical and cost-effective means of enhancing fraud detection effectiveness. Compared to more advanced AI applications, data analytics solutions are often easier to implement and integrate into existing audit workflows. Consequently, data analytics capability plays an important supporting role in strengthening fraud detection effectiveness, even though its statistical effect is not the strongest among the examined predictors.

5.4.3. The impact of auditor IT competence on fraud detection effectiveness

The findings further indicate that auditor IT competence has a positive and statistically significant effect on fraud detection effectiveness ($\beta = 0.368$, $p < 0.001$). This finding is consistent with prior research showing that auditors with stronger IT knowledge and skills are better able to apply computer-assisted audit techniques and to interpret technology-generated audit evidence when assessing fraud risks [10], [11].

Importantly, auditor IT competence appears to function primarily as an enabling capability that supports the effective use of audit technologies. Its contribution to fraud detection effectiveness depends on auditors' ability to integrate technological tools into audit workflows and to work with reliable, high-quality data [26], [28]. When auditors lack sufficient IT competence, the potential benefits of advanced technologies such as AI and data analytics may not be fully realized, as auditors may struggle to interpret analytical outputs or to appropriately rely on technology-based audit evidence.

Overall, this result suggests that auditor IT competence plays a complementary and facilitating role in strengthening fraud detection effectiveness. By enhancing auditors' capacity to utilize and interpret technology-based audit tools, IT competence reinforces the effectiveness of other technological resources and contributes to more robust fraud detection outcomes.

5.4.4. The impact of fraud detection effectiveness on audit quality

The results reveal a strong and positive relationship between fraud detection effectiveness and audit quality ($\beta = 0.741$, $p < 0.001$), highlighting fraud detection effectiveness as a central capability through which technological and human-capital resources contribute to audit quality. This finding is consistent with the Audit Risk Model, which emphasizes that improvements in audit quality arise primarily through the reduction of detection risk [1], [2]. By enhancing auditors' ability to identify and respond to fraud-related misstatements, higher fraud detection effectiveness strengthens the reliability of audit evidence and the appropriateness of audit opinions.

Prior studies similarly suggest that effective fraud detection enhances the credibility of audit outcomes by enabling auditors to focus audit efforts on high-risk areas and to exercise more informed professional judgment when assessing fraud risks [10], [39]. More recent evidence further indicates that technology-supported fraud detection plays an increasingly important role in improving audit quality by enhancing transparency and the quality of audit evidence in complex and data-intensive audit environments [29].

Importantly, the mediation analysis provides additional insight by demonstrating that fraud detection effectiveness fully mediates the effects of AI adoption, data analytics capability, and auditor IT competence on audit quality. From a Resource-Based View perspective, this result suggests that technological resources and IT-related skills do not enhance audit quality directly,

but instead contribute to audit outcomes through their transformation into an effective fraud detection capability [15], [16]. Consistent with agency theory, the findings further imply that technology reduces information asymmetry and agency costs only insofar as it enables auditors to detect and address fraudulent behaviour effectively, rather than through technology adoption per se [4], [17]. This result is also consistent with recent evidence indicating that AI adoption enhances audit outcomes primarily by strengthening fraud detection processes rather than directly improving audit quality [40].

Overall, these findings underscore the pivotal role of fraud detection effectiveness as the key mechanism linking technology-enabled audit resources to audit quality. They suggest that improvements in audit quality depend not merely on the adoption of advanced technologies, but on auditors' ability to deploy these resources in ways that meaningfully enhance fraud detection effectiveness.

5.4.5. Practical implications

Consistent with the identified full mediation effect, the findings provide several practical implications for audit firms and regulators, particularly in emerging markets. First, the strong influence of fraud detection effectiveness on audit quality suggests that audit firms should treat fraud detection as a core driver of audit quality rather than a supplementary activity. Investments aimed at improving fraud detection capabilities are therefore likely to yield substantial improvements in audit outcomes.

Second, although AI adoption exhibits the strongest statistical effect on fraud detection effectiveness, data analytics capability and auditor IT competence represent more immediately actionable enablers. Audit firms may benefit from prioritizing investments in analytics infrastructure and continuous training programs that enhance auditors' IT and analytical skills. These efforts can help ensure that advanced technologies are effectively utilized rather than underexploited.

Finally, regulators and professional bodies can support these initiatives by incorporating advanced analytics and IT competencies into auditing standards, certification requirements, and continuing professional education programs.

5.4.6. Limitations and future research

This study has several limitations that suggest avenues for future research. First, the use of cross-sectional survey data limits causal inference and generalizability beyond the Vietnamese context. Future studies could employ longitudinal designs or examine different institutional settings to validate and extend the findings.

Second, reliance on self-reported measures may introduce response bias. Future research could combine survey data with archival or experimental methods to enhance measurement robustness. Finally, future studies may extend the proposed framework by examining

moderating factors such as regulatory environments, data quality, or organizational culture to better understand the conditions under which technology most effectively enhances fraud detection and audit quality.

6. Conclusions

This study investigates how technological and human-capital resources contribute to audit quality by enhancing fraud detection effectiveness. Using survey data from external auditors in Vietnam and a PLS-SEM approach, the study provides empirical support for the proposed conceptual framework.

The findings indicate that AI adoption, data analytics capability, and auditor IT competence all significantly improve fraud detection effectiveness. AI adoption shows the strongest statistical effect, highlighting its potential to enhance auditors' ability to identify complex fraud patterns. Auditor IT competence plays an important enabling role by supporting the effective use of technology-based audit tools, while data analytics capability contributes by facilitating comprehensive data examination and proactive fraud risk assessment. Furthermore, fraud detection effectiveness is found to have a strong positive effect on audit quality, confirming its role as a central mechanism linking technological resources to audit outcomes.

From a practical perspective, the results suggest that audit firms should prioritize the development of fraud detection capabilities as a core driver of audit quality. While AI technologies offer substantial benefits, investments in data analytics infrastructure and continuous training to enhance auditors' IT competence may represent more feasible and immediate pathways, particularly in emerging markets.

This study is subject to limitations related to its cross-sectional design and reliance on self-reported data. Future research may extend the framework by using longitudinal data, alternative contexts, or examining moderating factors that influence the effectiveness of technology in auditing.

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