

# FRAUD DETECTION IN THE PROCESS OF COLLECTING AUDIT EVIDENCE: CONTRIBUTION TO HELPING FIRMS FULLY COMPLY WITH LEGAL REGULATIONS

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## Abstract

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According to Tran and Nguyen (2023), information technology (IT) plays an important role in all business activities, especially in the field of accounting and auditing. Nguyen et al. (2022) found that the auditor's responsibility affects fraud detection. The study examines the relationship between Vietnamese auditors' perceptions of using IT to detect fraud during the audit evidence collection process. Data was collected through a survey with 365 responses from auditors in Vietnam. Making use of a Likert scale with a range of 1 to 5, combined with a quantitative research approach, the findings reveal that auditors' perceptions of IT significantly influence its use in detecting fraud during evidence collection. The authors offer suggestions to improve auditors' use of IT in fraud detection based on the findings. Thereby contributing to improving corporate strategy and helping firms fully comply with legal regulations. Additionally, this work is a useful resource for researchers and auditing businesses, with theoretical and practical implications.

**Keywords:** Auditing, Auditors, Fraud, Information Technology, Corporate, Business Strategy

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## 1. INTRODUCTION

The study by Albrecht et al. (2011) suggests that fraud and the intention to continue committing fraud, whether driven by greed or influenced by seemingly trustworthy individuals, have serious consequences and remain an ongoing phenomenon that cannot be eliminated. Fraud is broadly defined as encompassing various methods employed by individuals to gain an advantage over others through misrepresentation, including deceptive and unfair practices.

In Vietnam, recent years have seen numerous cases of fraud in the preparation of financial statements by enterprises, such as Vien Dong Pharmaceutical Company in 2011 (SSC, 2011), Tay Bac Mineral Investment Joint Stock Company in 2012 (Chứng Khoán, 2016), and the Woodworking Industry Corporation in 2016 (Yến, 2016). These incidents have raised alarms about the quality of information in financial statements. In response, regulatory authorities have implemented various measures, including inspections, audits, and stricter requirements for public-interest entities to enhance the quality of their audited reports.

According to Ariga (2020), the conventional method of detecting fraud, which relies on auditors' retrospective assessments, is losing its effectiveness in today's digitally connected information environment. The advantages of computer-aided audit techniques, or "CAATs", in increasing audit efficiency have been the subject of numerous studies, which have shown that auditors' behavioral goals have a big influence on technology adoption. On the other hand, not much research has been done on the use of new technology for fraud detection.

In response, regulatory authorities have implemented various measures, including inspections, audits, and stricter requirements for public-interest entities to enhance the quality of their audited reports (Bari et al., 2024; Nguyen et al., 2024; Rosnidah et al., 2022).

However, minimal research has been conducted on the application of emerging technologies in fraud detection (Albahsh & Al-Anaswah, 2024).

From the above analysis, this study is necessary to carry out, which has both theoretical and empirical significance.

This research aims to identify the relationship between Vietnamese auditors' perceptions of using information technology (IT) to detect fraud during the audit evidence collection process. Subsequently, it seeks to propose solutions to enhance auditors' use of IT in fraud detection, thereby contributing to improving corporate strategy. The paper employed quantitative research methods to conduct the study. The recommendations provided serve as a valuable reference for auditing firms and researchers.

According to Tran and Nguyen (2023), IT plays an important role in all business activities, especially in the field of accounting and auditing. Based on data collected from internal auditors, directors, and department heads in joint stock companies in Hanoi, the authors used quantitative research to process the data. The results showed that IT is widely used in the auditing process. IT is especially used to create vouchers, books, and working papers of auditors. On the other hand, IT is also used by auditors and managers in the enterprise. Internal auditors use IT because it helps shorten the time of work and complete their work.

This research aims to explore auditors' perceptions of the usefulness of IT, perceived IT

competence, data quality, and professional skepticism in leading to fraud detection in audit testing. Data was collected through a survey with 365 responses from auditors in Vietnam. Using a Likert scale ranging from 1 to 5, combined with a quantitative research approach, the findings reveal that auditors' perceptions of IT significantly influence its use in detecting fraud during evidence collection. Based on the results, the authors provide recommendations to enhance auditors' use of IT in fraud detection.

The rest of the paper is structured as follows. Section 2 presents a review of the literature, which serves as the foundation for the current research model and the suggested research hypotheses. Section 3 describes the quantitative research approach. Section 4 provides the research findings. Section 5 discusses the results. Section 6 concludes the paper.

## 2. THEORETICAL FRAMEWORK

According to Columbus (2019), fraud and attacks are becoming more sophisticated, widespread, and scaled up than standard detection techniques can identify. Auditors must do their part to stay up to date on the newest technologies in order to detect fraud, since fraudsters are constantly modifying their methods to avoid discovery.

Furthermore, Hashim et al. (2019) underlined that since auditors are among the people most suited to spot fraud early on because of the nature of their employment, proactive steps in fraud detection are required of them. Auditors face increasing pressure to enhance their fraud detection capabilities, especially following the implementation of the International Standard on Auditing (ISA) 240.

Davis (1986) stated that perceived usefulness of a system is a belief that goes beyond observable phenomena, meaning it is the evaluation of the system's effectiveness without direct experience using the system. Users may highlight the perceived long-term benefits or utility of learning the technology when it is being implemented, as the emerging technology in this study is. Chau (2001) also pointed out that users' perceptions of the technology's usefulness might be influenced by its simplicity of use. Venkatesh et al. (2003) pointed out that productivity, efficiency, and job completion speed are all indicators of usefulness. Additionally, prior research has demonstrated that auditors' inclination to embrace technology is contingent upon their assessment of its utility (Bambang & Widya, 2019; Olanmi, 2013).

According to earlier quantitative research, Big Data analytics (Dagilienė & Klovienė, 2019) and embedded technology programs (Umar et al., 2017; Widuri & Gautama, 2020) both encourage audits and increase professional staff productivity. According to respondents' assessments of technology's utility, their desire to use it depended on its accessibility, as using IT in audit procedures helps auditors complete tasks while improving personal performance. According to Lee and Tajudeen (2020), artificial intelligence (AI) has shown a developing trend in accounting activities and can be applied in the auditing industry, which is challenging to test with conventional methods.

According to Bierstaker et al. (2014), the study, which included 31.1% participation from the Big 4, found that the longevity of performance related to users' perceptions of using the system led to performance affecting auditors' technology use. Despite being rated as helpful by accountants,

the use of data mining processes, filtering software, and digital analytic approaches was shown to be rare in detecting fraudulent transactions.

One of the primary reasons IT is utilized is to reduce obstacles and enhance audit quality, which is connected to fraud detection (Olasanmi, 2013; Umar et al., 2017; Abou-El-Sood et al., 2015; Widuri & Gautama, 2020). However, Pham et al. (2018) found that the use of technology in fraud detection was deemed the least important. These studies had fewer than 50% respondents from Big 4 firms.

Significant benefits promised by emerging technologies have driven changes in the way audits are evaluated, alongside the need for auditors to develop the necessary skills to adapt to technological innovations. As their time progressively shifts to value-added components beyond normal activities, auditors must adjust to these developments (Association of Chartered Certified Accountants [ACCA], 2019). Sufficient IT skills are necessary to implement and interpret the outputs of these technologies (Siew et al., 2020). Studies have shown that the impact on users' system usage is positively contributed by their perceptions of simplicity (Chafik & Mghizou, 2018).

Albahsh and Al-Anaswah's (2024) research provides an in-depth examination of the role AI plays in revolutionizing bank auditing and quality control processes. This systematic mapping study (SMS) explores the extent of AI's adoption in bank audits, specific areas of its application, its impact on auditing processes, challenges, and the dynamics of human-AI collaboration in auditing. The findings reveal AI's pivotal roles in enhancing credit risk analysis, operational efficiency, fraud detection, cybersecurity, and bankruptcy prediction, through analyzing complex data, identifying patterns, and ensuring financial stability, which leads to streamlining operations, detecting fraudulent activities through advanced pattern recognition, boosting cybersecurity measures, and accurately forecasting bankruptcy risks, thereby offering a robust tool for risk management and decision-making in the banking sector.

The alignment of tasks with technology, combining auditors' knowledge with the perceived importance of technology, has revealed a gap through past research. Al-Duwaila and Al-Mutairi (2017) and Ismail and Abidin (2009) discovered that auditors in Kuwait and Malaysia, respectively, placed less value on understanding system design and implementation, office automation, accounting office automation, and audit automation. Payne and Curtis (2017) evaluated the gap and found a relationship between the intention to use and the intention to train on optional technologies. They found that auditors plan to improve their technology abilities through training to make using technology during the audit process easier. When auditors find technology useful for their everyday work, they start using it to improve forecasts and analysis, which increases the ability to discover fraud through audit testing (ACCA, 2019).

According to Abou-El-Sood et al. (2015) and Pham et al. (2018), those who have more IT knowledge and skill find technology easier to use and worry less. Furthermore, quantitative research of Big 4 auditors in Indonesia demonstrated how IT expertise and proficiency affect fraud detection through the use of modern technologies for data identification, analysis, and testing (Fadilah et al., 2019). Olasanmi (2013) stated that to detect fraud, employees must be proficient in the use of digital forensic tools, analysis methods, and investigative

tools (Susanto et al., 2019), all of which are connected to the collection of evidence during audits.

Even though AI developers recognize the value of data and devote substantial resources to data-related tasks, most businesses have failed to maintain the quality of data, which is essential for the development of AI systems (Sambasivan et al., 2021). Even with the speed, diversity, and volume of data that modern technologies can provide, their quality is still seen as lacking (Ghasemaghahi & Calic, 2019). The availability of data, that is, how hard it is to get data and how quickly it can be obtained to guarantee significant results, is the basis for evaluating the dimensions of data quality. The term "usability" refers to the source's dependability, which is related to the data's completeness, consistency, and integrity, as well as its relevance to the user's demands and format clarity (Cai & Zhu, 2015). Taleb et al. (2018) have noted that assessing quality is difficult because of the different kinds of data structures that Big Data has provided. These data structures vary in complexity but do not yet have clear standards for quality management. To guarantee that machine learning systems can provide precise forecasts and predictions while avoiding the problems of garbage in, garbage out, data quality is also a crucial consideration (Sambasivan et al., 2021).

Data quality problems, which can result from a variety of sources, including incorrect input or subpar system design, have an impact on decision-making abilities (Ghasemaghahi & Calic, 2019). According to Ghasemaghahi and Calic (2019), decision-making can be aided by organizational objectives to rapidly acquire detailed insights through data accumulation, as this can aid in carefully examining the findings of conventional analysis. As a result, this makes it possible for auditors to examine past financial data from clients, which is subsequently bolstered by further information gleaned from developing technologies, to ascertain whether it presents a fair and accurate picture as well as any potential inaccuracies brought on by fraud or misinterpretation.

The quality of data from financial information sources has to be evaluated and tested as the review process becomes more automated and continuous (Chartered Professional Accountants of Canada [CPA Canada] & the American Institute of CPAs [AICPA], 2017). Since the accuracy of testing is heavily dependent on the inputs, CPA Canada and AICPA (2020) later confirmed that the support of emerging technologies in accessing external data, such as industry trends for subsequent analysis, has shifted the attention to data quality. According to Sambasivan et al.'s (2021) "garbage in, garbage out" theory, data quality will be harmed in the absence of sufficient internal controls to guarantee operational effectiveness. This will have an impact on the significance of financial reporting since the output may be imprecise or unable to correctly identify fraudulent transactions in the audited organization.

To perform their tasks effectively, auditors must use professional skepticism, which suggests that they should presume that management is not being totally truthful when they provide audit explanations (Kusumawati & Syamsuddin, 2018). This study emphasizes that a lack of professional skepticism leads to the failure to recognize problems and, consequently, to take action on them (Chiang, 2016). Because the selected audit plan will be extremely relevant in addressing the risks presented by the examined organization,

auditors are an effective and efficient tool in uncovering fraud if skepticism is applied (Carpenter & Reimers, 2013).

Since auditors may assume that enough work has been done, backed up by evidence, and that no mistakes resulting from potentially concealed fraudulent items have occurred, the complexity of accounting makes it harder for them to maintain professional skepticism (Kleinman et al., 2020). Lee and Tajudeen (2020) and Kantonenko and Karlström (2020) claim that technology makes it simple for auditors to go from simpler to more difficult jobs, such as comprehending the risks that customers can encounter, which calls for a greater degree of skepticism. The possibility of finding mistakes and discrepancies is increased when auditors examine working papers and auditing evidence with greater skepticism (Hurt et al., 2013).

In a similar vein, Kusumawati and Syamsuddin (2018) discovered that the professional skepticism of Indonesian auditors influences the attitude of professional skepticism toward audit quality (Chiang, 2016) and mediates the association between auditor quality and audit quality. According to Hussin et al. (2017), this implies that auditors who value professionalism throughout the audit process maintain skepticism regarding the assessment of audit evidence. This helps to improve audit quality and prevent fraud detection failures, while also lowering the risk of issuing an inappropriate audit opinion.

However, professional skepticism had no discernible effect on the ability to identify fraud (Indrasti & Karlina, 2020). This indicates that the study's auditors thought fraud might be found without challenging the client's justifications.

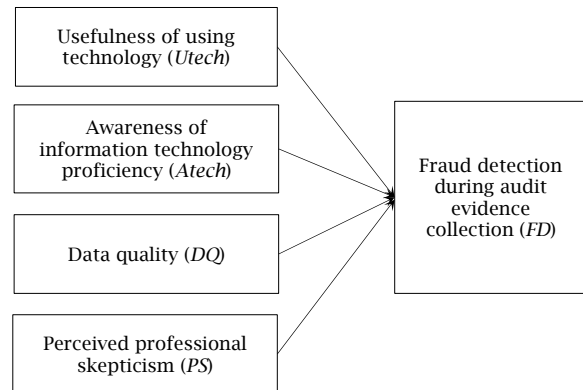
The purpose of Nguyen et al.'s (2022) study is to review the relationship between the effectiveness of the internal audit and the auditor's responsibility in fraud detection of the enterprises. The sample includes 176 internal auditors working in the listed firms in Vietnam. The data were analyzed by SPSS 22 software. The results show that the internal audit effectiveness, the auditor's responsibility, and auditor training have a positive and significant effect on fraud detection.

Bari et al. (2024) explored how internal auditing regulates corruption, enhances corporate governance, and investigates the potential of internal auditing as a means to combat corruption. Additionally, the report explores the potential benefits of implementing advanced technology, data analytics, and continuous monitoring to enhance internal audits. The findings of the study demonstrate that internal auditing is an essential component in the fight against corruption and the maintenance of good corporate governance. In doing so, it highlights the significance of having strong internal audit functions as well as a culture that is both ethical and open. The conduct of internal audits has the potential to improve corporate governance, reduce instances of misconduct, and ensure that a business will continue to be profitable in the future.

Nguyen et al. (2024) investigated the relationship between variables such as the quality of internal audit, the capability of the internal audit team, the independence of internal audit, and the support of leadership on the effectiveness of internal audit (EIA). Data were gathered through a survey of 325 questionnaires from joint stock firms in the context of Vietnam, using SPSS 22 software and SmartPLS 3.0 software to analyze the regression of influencing determinants. The results reveal that:

1) the quality of the internal audit, the capability of the internal audit team, the independence of the internal audit, and the support of leadership affect the internal audit effectiveness; 2) the EIA, the responsibility of auditors, and auditor training have a positive and significant effect on fraud detection. Therefore, the importance of internal audit in identifying accounting fraud and the need for firms to design internal audit processes and training to improve the effectiveness of their operations are highlighted. From there, the authors propose a research model in Figure 1.

**Figure 1.** Research model



Based on the relevant literature (Davis, 1986; Bambang & Widya, 2019; Olasanmi, 2013; Dagilienė & Klovienė, 2019; Lee & Tajudeen, 2020; Bierstaker et al., 2014; Abou-El-Sood et al., 2015; Umar et al., 2017), the first research hypothesis is as follows:

*H1: The detection of fraud during the audit evidence collection process is correlated with auditors' perceptions of the value of adopting technology.*

Based on the previous studies (ACCA, 2019; Siew et al., 2020; Chafik & Mghizou, 2018; Ismail & Abidin, 2009; Al-Duwaila & AL-Mutairi, 2017; Payne & Curtis, 2017; Abou-El-Sood et al., 2015; Pham et al., 2018; Fadilah et al., 2019; Olasanmi, 2013), the second hypothesis is:

*H2: There is a relationship between auditors' perception of IT proficiency in relation to the emergence of technology and the detection of fraud during the audit evidence collection process.*

Based on Ghasemaghahi and Calic (2019), Sambasivan et al. (2021), Cai and Zhu (2015), Taleb et al. (2018), and CPA Canada and AICPA (2017), the third hypothesis is as below:

*H3: There is a relationship between the quality of auditors' data about the development of technology and the identification of fraud during the audit evidence collection procedure.*

Based on Kusumawati and Syamsuddin (2018), Chiang (2016), Carpenter and Reimers (2013), and Indrasti and Karlina (2020), the fourth hypothesis is:

*H4: Fraud detection throughout the audit evidence collection process is correlated with auditors' professional suspicion regarding the usage of IT.*

### 3. RESEARCH METHODOLOGY

#### 3.1. Data collection

By in-depth interviews with business managers, including directors, deputy directors, department heads, and auditors working in Vietnam. Mainly in Vietnam. Experts, experienced auditors, and

university auditing lecturers were also interviewed. The interview method aims to collect information on the characteristics of each factor affecting the relationship between auditors' perceptions of the usefulness of IT, assessed IT capabilities, data quality, and professional skepticism in detecting fraud during auditing in Vietnam. From the factors identified in the literature review, a quantitative survey questionnaire was distributed to the identified respondents using various methods: 1) direct delivery, 2) mail, 3) email, 4) Google Docs, and 5) others. A total of 421 responses were collected out of 435 questionnaires distributed. After excluding invalid responses due to missing or incomplete information, the authors retained 365 valid responses, achieving a response rate of 83.31%.

### 3.2. Data processing

The authors utilized SPSS 22 software for data analysis, employing key metrics such as mean, median, maximum value, minimum value of the study variables, and standard deviation to measure data variability. To learn more about the characteristics of the research data, descriptive statistical analysis was carried out, concentrating on particular variables and the dataset's primary tendencies.

To evaluate the quality of the scales, the authors applied Cronbach's alpha. A scale is considered to be of good quality when: 1) the corrected item-total correlation of observed variables is greater than 0.3 and 2) the overall Cronbach's alpha coefficient is greater than 0.6 (Nunnally & Bernstein, 1994).

To extract components for additional research, exploratory factor analysis (EFA) was then carried out. The factor loading metric was used to assess the significance of EFA coefficients. According to Hair et al. (1998), a factor loading greater than 0.3 is considered the minimum threshold, greater than 0.4 is considered significant, and greater than 0.5 is considered practically meaningful.

In this study, to enhance the reliability and practical relevance of the results, only factors with loadings greater than 0.5 were selected. The Kaiser-Meyer-Olkin (KMO) measure ensured values within the range of  $0.5 \leq KMO \leq 1$ , and the total variance explained exceeded 0.5 during EFA. Additionally, the study applied the principal component analysis (PCA) method and Varimax rotation to extract key factors.

The proposed research model was based on the EFA results. After being separated into primary factor categories, the extracted factors were coded as either independent or dependent variables. The study used a multiple regression analysis model to determine the parameters of the factors used in the model in order to evaluate the degree of connection between the factors and the usage of IT in internal auditing.

## 4. RESEARCH RESULTS

### 4.1. Descriptive statistics

The values of the factors of the utility of technology use range from 1 to 5. According to Table 1, *Utech2* has the greatest mean value of 3.67 among these, while *Utech9* has the lowest mean value of 3.44.

**Table 1.** Descriptive statistics for variables usefulness of using technology (*Utech*)

Variables	N	Min	Max	Mean	Standard deviation
<i>Utech1</i>	365	1	5	3.45	0.843
<i>Utech2</i>	365	1	5	3.67	0.784
<i>Utech3</i>	365	1	5	3.50	0.837
<i>Utech4</i>	365	1	5	3.47	0.775
<i>Utech5</i>	365	1	5	3.55	0.797
<i>Utech6</i>	365	1	5	3.54	0.822
<i>Utech7</i>	365	1	5	3.51	0.791
<i>Utech8</i>	365	1	5	3.52	0.803
<i>Utech9</i>	365	1	5	3.44	0.797
Valid N (listwise)	365				

Source: Analysis results from SPSS 22.0.

Similarly, other scales, such as perception of information technology proficiency (*Atech*), range from 1 to 5. Among these, *Atech5* has the highest mean value of 3.74, and the lowest is *Atech7* with a mean of 3.12.

Data quality (*DQ*) also ranges from 1 to 5. Among these, *DQ3* has the highest mean value of 3.81, and the lowest is *DQ8* with a mean of 3.21.

Perceived professional skepticism (*PS*) ranges from 1 to 5. Among these, *PS1* has the highest mean value of 3.92, and the lowest is *PS6* with a mean of 3.11.

Fraud detection in the audit evidence collection process (*FD*) ranges from 1 to 5. Among these, *FD5*

has the highest mean value of 3.76, and the lowest is *FD10* with a mean of 3.06.

### 4.2. Scale check

The Cronbach's alpha reliability coefficient and EFA analysis were used to examine the scale for the impact of IT on internal auditing. The item-total correlation coefficients for the scales are all greater than 0.3, and Table 2 demonstrates that the majority of the components have Cronbach's alpha values greater than 0.6, after excluding the observed variables, including *Utech1*, *Utech3*, *Atech2*, *Atech5*, *Atech7*, *DQ4*, *DQ5*, *FD3*, and *FD8*.

**Table 2.** Cronbach's alpha coefficient results of the scales

Variables	Number of variables Observe		Cronbach's alpha	Minimum total correlation coefficient
	Before	After		
<i>Utech</i>	9	7	0.734	0.685
<i>Atech</i>	9	6	0.797	0.613
<i>DQ</i>	8	6	0.845	0.721
<i>PS</i>	8	8	0.890	0.657
<i>FD</i>	10	8	0.867	0.657

Source: Analysis results from SPSS 22.0.

### 4.3. Exploratory factor analysis and correlation between variables

#### 4.3.1. The Kaiser-Meyer-Olkin and Bartlett tests

The KMO index is 0.862, which is higher than 0.5, according to the factor analysis results (Table 3), suggesting that the data used for the factor analysis is extremely appropriate.

With a significance level of p-value,  $\text{sig.} = 0.000 < 0.05$  and a Bartlett's test result of 1569.327, the null hypothesis ( $H_0$ : The observed variables are uncorrelated in the population) is rejected. The variables are correlated with one another and satisfy the requirements for factor analysis, thereby rejecting the hypothesis that the correlation matrix of the variables is an identity matrix.

**Table 3.** KMO and Bartlett coefficients

Targets	Model
KMO	0.862
Bartlett	1,569.327
The Bartlett test has a sig. value	0.000
Total value of variance extracted	57.254
Minimum eigenvalues	1.219

Source: Analysis results from SPSS 22.0.

After eliminating the scales that failed to meet reliability standards, the results indicate that the total variance explained for the remaining observable variables is 57.254%, meeting the  $> 50\%$  threshold. This means that these factors explain 57.254% of the variability in the data. The eigenvalues of the factors are all high ( $> 1$ ), with the lowest eigenvalue being 1.219, which satisfies the condition of  $> 1$ .

Thus, the EFA is appropriate for the data, and the observed variables are correlated with each other in the population, making it suitable for further analysis.

The EFA was conducted using the component analysis extraction method and Varimax rotation. The analysis results show 35 observed variables for the independent variables, as presented in Table 4.

**Table 4.** EFA of independent variables: Rotated component matrix<sup>a</sup>

Variables	Component				
	1	2	3	4	5
Utech2			0.621		
Utech4			0.492		
Utech5			0.482		
Utech6			0.547		
Utech7			0.632		
Utech8			0.524		
Utech9			0.598		
Atech1		0.684			
Atech3		0.751			
Atech4		0.465			
Atech6		0.587			
Atech8		0.734			
Atech9		0.654			
DQ1	0.498				
DQ2	0.656				
DQ3	0.757				
DQ6	0.734				
DQ7	0.787				
DQ8	0.714				
PS1				0.654	
PS2				0.602	
PS3				0.812	
PS4				0.767	
PS5				0.759	
PS6				0.664	
PS7				0.741	
PS8				0.736	
FD1					0.725
FD2					0.714
FD4					0.707
FD5					0.647
FD6					0.684
FD7					0.514
FD9					0.691
FD10					0.645

Note: Extraction method: Principal component analysis (PCA). Rotation method: Varimax with Kaiser normalization. a. Rotation converged in 5 iterations.

#### 4.3.2. Correlation analysis between variables in the model

The correlation coefficients between the variables are shown in Table 5. Before executing the regression model, it is important to make sure

that there is a significant correlation between the independent and dependent variables in order to rule out any potential causes of multicollinearity. The findings demonstrate that there is a correlation between the dependent variable and the four independent factors, as each has a sig. coefficient

less than 5%. The correlation coefficients for the four factors are: *Utech*: 0.312, *Atech*: 0.411, *DQ*: 0.221, *PS*: 0.169. The correlation between these four independent variables in the model does not have any pairs greater than 0.8, so when using

the regression model, the likelihood of encountering multicollinearity is low. This indicates that the dependent variable has a linear correlation with the three factors, and these variables follow a normal distribution.

**Table 5.** Correlation matrix

		<i>FD</i>	<i>Utech</i>	<i>Atech</i>	<i>DQ</i>	<i>PS</i>
<i>FD</i>	Pearson correlation	1	0.312	0.411	0.221	0.169
	Sig. (2-tailed)		1	1	1	1
	N	365	365	365	365	365
<i>Utech</i>	Pearson correlation	0.312	1	0	0	0
	Sig. (2-tailed)	1		1	1	1
	N	365	365	365	365	365
<i>Atech</i>	Pearson correlation	0.411	0	1	0	0
	Sig. (2-tailed)	1	1		1	1
	N	365	365	365	365	365
<i>DQ</i>	Pearson correlation	0.221	0	0	1	0
	Sig. (2-tailed)	1	1	1		1
	N	365	365	365	365	365
<i>PS</i>	Pearson correlation	0.169	0	0	0	1
	Sig. (2-tailed)	1	1	1	1	
	N	365	365	365	365	365

Source: Analysis results from SPSS 22.0.

#### 4.4. Multivariate linear regression analysis

The authors employ multiple linear regression between the four influencing factors derived from

the factor analysis and correlation analysis above in order to identify, quantify, and assess the influence of factors on internal audit.

**Table 6.** Multivariable regression results

	Unnormalized coefficients		Normalization coefficient	Value t	Sig	Multicollinearity	
	B	Standard deviation	Beta			Acceptability	VIF
Constant	3.4641	0.054		48.23	0.000		
<i>Utech</i>	0.301	0.040	0.322	4.542	0.000	0.747	1.112
<i>Atech</i>	0.343	0.031	0.201	4.351	0.000	0.804	1.427
<i>DQ</i>	0.210	0.022	0.214	3.661	0.000	0.621	1.354
<i>PS</i>	0.212	0.021	0.194	3.652	0.000	0.521	1.397
R <sup>2</sup>							0.547
R <sup>2</sup> correction							0.485
Sig. F change							0
Durbin-Watson							2.112

Source: Analysis results from SPSS 22.0.

The regression findings in Table 6 reveal that the R<sup>2</sup> value is 0.485, meaning that 48.5% of the variation in the dependent variable can be explained by the independent variables in the model. At the same time, the analysis results show that the variance inflation factor (VIF) is very small, all less than 2, indicating that these independent variables do not have a strong relationship with each other, and thus multicollinearity does not occur.

Regarding the independence test of the residuals, the Durbin-Watson statistic of the regression function is 2.112, which is less than 3, showing that there is no first-order autocorrelation. In other words, the estimated residuals of the model are independent and have no linear relationship with each other. The t-values corresponding to the sig. values for the independent variables are all smaller than 0.05, indicating statistical significance.

From Table 6, it can be seen that four factors influence the detection of fraud during the audit evidence collection process. The regression equation for these variables is as follows:

$$FD = 3.4641 + 0.301 * Utech + 0.343 * Atech + 0.210 * DQ + 0.212 * PS \quad (1)$$

*H1*, *H2*, *H3*, and *H4* are accepted. That is, the usefulness of using technology (*Utech*), perception of information technology proficiency (*Atech*), data quality (*DQ*), and perceived professional skepticism (*PS*) have an impact on fraud detection during the audit evidence collection process (*FD*).

This is synonymous with previous studies such as Davis (1986), Bambang and Widya (2019), Olanmi (2013), Dagilienė and Kloviene (2019), Lee and Tajudeen (2020), Bierstaker et al. (2014), Abou-El-Sood et al. (2015), Umar et al. (2017), ACCA (2019), Siew et al. (2020), Chafik and Mghizou (2018), Ismail and Abidin (2009), Al-Duwaila and Al-Mutairi (2017), Payne and Curtis (2017), Pham et al. (2018), Fadilah et al. (2019), Ghasemaghaei and Calic (2019), Sambasivan et al. (2021), Cai and Zhu (2015), Taleb et al. (2018), CPA Canada and AICPA (2017), Kusumawati and Syamsuddin (2018), Chiang (2016), Carpenter and Reimers (2013), Kusumawati and Syamsuddin (2018), and Indrasti and Karlina (2020).

However, it is in contrast to the study by Indrasti and Karlina (2020) of auditors in a public accounting firm in Jakarta, where it is found that professional skepticism had no significant impact on the ability to detect fraud. This means that auditors involved in the study believed that fraud could be detected even without questioning the client's explanations.



## 5. DISCUSSION

Based on the research results, the usefulness of using technology (*Utech*), perception of information technology proficiency (*Atech*), data quality (*DQ*), and perceived professional skepticism (*PS*) have an impact on fraud detection during the audit evidence collection process (*FD*).

The results show that *Utech* has the greatest impact on *FD* ( $\beta = 0.324$ ). Next, *Atech* ( $\beta = 0.365$ ). This means that both *Utech* and *Atech* impact *FD*. Specifically, the surveys show that when technology is applied in auditing, it can address work-related needs and support important aspects of the job, reducing time spent on ineffective activities with the use of emerging technologies. Additionally, auditors believe that technology facilitates their evaluation and auditing work, reducing barriers and raising audit quality in relation to fraud detection, which in turn improves the efficiency of corporate operations.

Furthermore, in order to identify fraud and inaccuracies in financial accounts, auditors must uphold professional skepticism in accordance with Vietnamese Auditing Standard No. 240. Throughout the audit process, auditors must constantly maintain a professional skepticism, particularly when conducting an audit in an IT environment.

Based on this, the authors recommend the following:

For businesses, they should apply technology in the auditing environment. Training is required to improve auditors' abilities and expertise, particularly in light of emerging technologies and numerous fraudulent schemes. Additionally, businesses should consider allocating time appropriately for audit evaluation. Creating a healthy, competitive, and fair working environment is also essential.

For auditors, they should always learn, participate in refresher courses, and stay updated with new application software. In particular, auditors must maintain professional skepticism throughout the audit process.

## 6. CONCLUSION

This study aims to examine the factors that auditors at audit firms in Vietnam perceive to influence the use of IT to detect fraud during audits. Specifically, this study aims to understand auditors' perceptions of the usefulness of IT, perceived IT capabilities, data quality, and professional skepticism in detecting fraud during audits. This study lays the foundation for future studies, such as: Does digital transformation increase fraud in auditing, or the role of information technology in digital transformation at audit firms? However, this study is limited to auditors operating in the Vietnamese context. Future studies could expand the scope by incorporating additional financial indicators or examining alternative dependent and control variables that influence the relationships between auditors' perceptions of the usefulness of IT, perceived IT competence, data quality, and professional skepticism in detecting fraud during audits.

Furthermore, although this study makes some recommendations regarding these factors, it does not delve into the underlying causes that limit auditors' perceptions and competencies in these areas. The discussion of these limitations is only briefly mentioned. Further studies could adopt qualitative research methods to gain a deeper understanding of the barriers that influence auditors' perceptions of the usefulness of IT, IT competence levels, data quality issues, and the application of professional skepticism. These insights can contribute to improving audit effectiveness and minimizing the risk of material misstatement or fraudulent reporting in enterprises.

Although the research results show that auditors' awareness of IT significantly affects the use of IT in detecting fraud during the evidence collection process, serving as a valuable reference for researchers and business managers, this study is still limited in terms of research sample and research space. Therefore, in the future, there is still a need for more in-depth research, as well as expanding the research sample and research space.

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