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THE EFFECT OF AUDITOR EXPERIENCE, BIG DATA AND FORENSIC AUDIT AS MEDIATING VARIABLES ON FRAUD DETECTION

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ABSTRACT

The many cases of fraud in Indonesia caused losses to the state. It has driven stakeholders, including the Government, to determine effective and efficient methods to detect fraudulent issues. Therefore, this study aimed to examine the influence of auditor experience, Big Data, and forensic auditing as mediating variables on fraud detection. It used a quantitative approach with a survey method by distributing questionnaires through a google form. Respondents comprised 128 internal, external, and government auditors. Furthermore, the data were analyzed using structural equation modeling (SEM) with the help of SmartPLS tools. The results showed that the auditor's experience, forensic audit, and Big Data positively and significantly affect fraud detection. Auditor experience and Big Data variables positively and significantly affect Forensic Audits. Additionally, a forensic audit mediates the auditor's experience with fraud detection but does not mediate Big Data against fraud detection.

Keywords: *Auditor Experience, Big Data, Forensic Audit, Fraud Detection*

1. INTRODUCTION

In the current industrial revolution 4.0 era, digital developments increase the possibility of economic fraud risk. It has driven many stakeholders, including the Government, to seek effective ways to detect fraud. The stakeholders aim to minimize fraudulent acts due to their extraordinary impact. Indonesia is one of the countries with high corruption cases. According to [1], the anti-corruption non-governmental organization Indonesia Corruption Watch (ICW) predicted 209 corruption cases in 2021, with a total state loss of 26.83 trillion. ICW reported that the most corrupt perpetrators were civil servants (ASN), the private sector, and village heads, with 124, 77, and 44 suspects, respectively [2].

Fraud is a problem that still occurs today. Various cases, such as corruption, robbery or fraudulent financial statements, and asset thefts, are complex or cannot be detected by conventional financial inspection processes. It requires unconventional inspection techniques following their authority, such as big data analysis, computer forensics, and forensic intelligence. Based on International Standards on Auditing (ISA) 240, fraud is an act intentionally carried out by management in a company, people involved in corporate governance, third parties, or employees who commit fraud to gain unlawful or unfair advantages. Fraudulent acts are often caused by pressures that affect individuals, rationalizations, or opportunities.

Moreover, frauds occur in companies or organizations but are not reported for fear of unfavorable consumer or stakeholder reactions, a bad company image, insufficient evidence, or a reluctance to waste time and energy investigating the cases [3]. This fraud case is troubling to many parties, especially the Government. One factor that could detect fraud is the auditors' experience. Auditors could detect fraud because more experience produces more knowledge [4]. They must have sufficient expertise to find fraud in an organization. More experience enables auditors to deliver accusations in explaining audit findings to improve their ability to detect fraud [5].

Fraud detection is influenced by the auditors' experience and other factors and could be detected using many methods. However, the most effective and efficient method helpful in detecting fraud is still being searched [6]. Big Data is useful in

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detecting an organization's fraud [7]. It could be used directly to detect fraud and increase the effectiveness of fraud detection methods. It is because auditors could maximize the benefits of comprehensive data contained in Big Data using data analytics tools. They could easily analyze fraud risks in an organization and investigate the causes. Auditors usually cannot detect fraud because they only analyze unstructured and non-financial data, such as contract details, meeting results, and management-related communications. Therefore, Big Data could solve this problem with the capabilities of data analysis tools.

Big Data is an excellent opportunity for auditors to facilitate their work in detecting fraud, including forensic audits. According to [8], forensic auditing is an effective and efficient tool for detecting, preventing and reducing fraud. Therefore, an organization should embrace the forensic audit factor to quickly detect and adequately prevent fraud cases. Several reasons make this audit an effective method for detecting fraud. First, [9], [10] stated that forensic audits are effective because it is devoted and focused on investigating and detecting fraud. Second, forensic auditors should be knowledgeable in many scientific fields, such as information technology, investigation skills, law, and finance. There are high demands to become auditors because the audit is evidence in the litigation process. Third, forensic audits use a proactive approach to identify the various potentials for the possibility of fraud. They also use a reactive approach to determine possible fraudulent acts that have already occurred.

Based on the background, this study aimed to examine the effect of auditors' experience, Big Data, and forensic audits on fraud detection. It also intended to investigate the role of forensic audits in mediating the impact of auditors' experience and Big Data on fraud detection. The respondents comprised internal, external, and government auditors. Studies in Indonesia rarely examine auditors' experience factors, Big Data, and forensic audits and their influence on fraud detection. The studies also hardly test these three factors simultaneously to detect fraud. The following are several studies that analyze fraud detection related to [6], [7], [8] and [10]

Furthermore, the effect of auditors' experience and Big Data on forensic audits has not been investigated. It is reasonable that these factors are influential in enhancing the role of audits in detecting fraud. Therefore, this study is expected to develop effective methods and models to detect fraud. Internal, external, and government auditors could use the results to detect and disclose fraud.

2. LITERATURE REVIEW

2.1. Agency Theory

According to [11], agency theory combines economic, decision, sociology, and organizational theories and raises two problems. First, information asymmetry occurs because management knows more about the organization's financial position and operations. Second, conflicts of interest occur because of differences in objectives. Disputes arise when agents do not execute orders from the principals on their behalf. Furthermore, agents with power in an organization as decision-makers are interested in maximizing the institution's profits with the policies issued. It shows that agency theory is a condition that leads to fraud in an organization. The agent has asymmetric information and takes advantage of the existing fraud by manipulating the organization's financial statements. Therefore, competent and skilled auditors are needed to detect and prevent fraud.

2.2. Fraud Detection

According to [12], fraud is an unlawful act requiring special skills to profit from the victim. Someone commits fraud due to pressure, opportunity, rationalization, competence, and arrogance. These five factors are called the fraud pentagon, a development of the fraud triangle, and the previous theory of the causes of fraud [13].

2.3. Auditor Experience

Experience is essential in detecting fraud because it takes an auditor's expertise and knowledge to make an assumption. The auditor's experience is seen in the length of work and the number of assignments and studies of the same problem [14]. Work experience shapes people to be better at work and is calculated based on time or years of work. The increasing experience makes the individual faster, more proficient, and superior in completing each task [15]. It benefits people carrying out their work, including auditors.

2.4. Big Data

According to [16], Big Data is a large, more varied, complex data set generated from information collected in one integrated container from many sources. These may include online and mobile transactions, social media, videos, web, and applications. These data are stored in databases that grow massively and become difficult to capture, store, manage, share, analyze, and visualize through the usual software tools [16]. Big Data is beneficial in the disruption era because everything uses information technology [17]. It helps auditors improve the quality of audit evidence, detect fraud, and contribute to auditing. Also, it provides extensive data, where auditing is based on a sample and a population basis.

2.5. Forensic Audit

The use of auditors to carry out forensic audits has increased. Forensic audits include collecting, verifying, processing, analyzing, and reporting data to obtain facts and tangible evidence in legal and financial disputes, irregularities, and fraud prevention [18]. These activities focus on detecting, analyzing, communicating, and reporting the evidence on which a financial event is based [19]. Forensic auditing involves collecting and assessing the suitability of the evidence during the trial process. It is an extension of standard audit procedures to collect evidence required in court proceedings. The forensic examination includes specific steps carried out to provide evidence. The steps and methods aim to detect and investigate fraud by uncovering its actions and identifying the perpetrators [20].

2.6. Conceptual Framework

Figure 1 shows this study's conceptual framework, describing auditor experience, Big Data, and forensic audit as mediating variables in fraud detection.

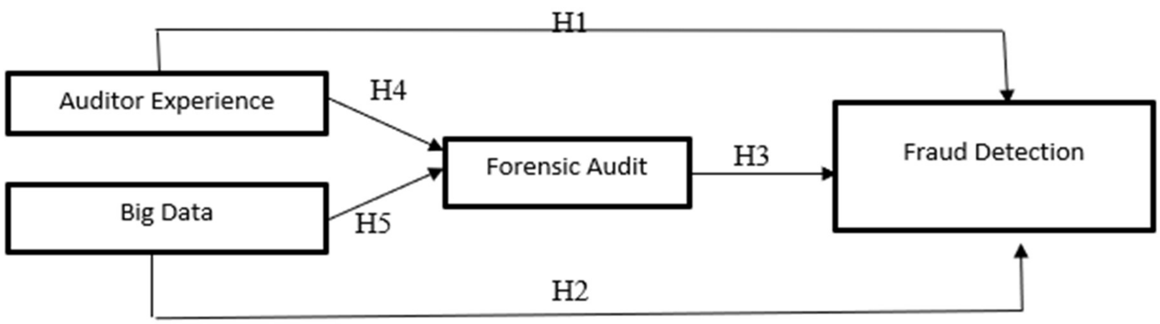

Figure 1: Conceptual Framework
Source: Processed by Researcher, 2022

2.7. Hypothesis

The auditor's experience is seen in their work tenure, assignments, and reviewing problems [14]. More experience enables auditors to detect fraud easily during the audit process. Auditor experience measures the time and period of work people have passed in understanding their job duties correctly. According to [21], experience influences the auditor's ability to detect fraud because it deepens and broadens work skills. The more often auditors perform the same task; the faster and more skilled they are in carrying out their work. Experienced auditors also better understand the causes of human, tool, or intentional errors, implying fraud [22]. According to [23] found that auditor experience positively affected fraud detection. The study contradicts [24], which showed that the auditor's work experience positively but insignificantly influenced fraud detection. Therefore, the hypothesis was formulated as follows:
H_1: Auditor experience positively and significantly affects fraud detection.

According to [25], Big Data expands the source and size of information auditors need to detect fraud. It supports the analytical process and improves the quality of fraud detection results. It is in line with agency theory, where Big Data overcomes agency problems or fraud in an organization [25]. According to [7], Big Data speeds up data creation and improves visualization results and internal team communication in fraud detection. It allows data integration into the system, and Alibaba is an example of a large company proving the benefits of the integration to detect and combat fraud [26].

Moreover, [27] found that 72% of 466 companies stated that Big Data technology is crucial in preventing and detecting fraud. It shows that it is an efficient and effective tool for fraud detection. [28] also found that Big Data effectively and efficiently detected fraud. Therefore, the hypothesis was formulated as follows:

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H2: Big Daa positively and significantly affects fraud detection

According to [18], a forensic audit entails collecting, verifying, processing, analyzing, and reporting data. The process aims to obtain legally valid facts and evidence and advise on preventing an illegal case or financial irregularity, including fraud. Since the collected evidence must be legally valid, the assigned auditor must have a mature strategy supported by unquestionable knowledge, skills, and experience. Forensic auditors must master various branches of science, such as accounting, information technology, and criminology [29]. It makes forensic audits one of the best audits helpful in detecting and revealing fraud. According to [6], [18], [30] also proved the effectiveness of forensic audits in detecting fraud. Therefore, the hypothesis was formulated as follows:

H3: Forensic audit positively and significantly affects fraud detection

Experience is the expertise and knowledge obtained through direct observation or participation in various events [22]. The increasing experience makes individuals faster, more proficient, and superior in completing tasks [15]. It helps individuals carry out their work, including the auditors. Experienced auditors are critical to the success or failure of special and risk-filled fraud audits, such as forensic and investigative audits [31]. Therefore, the hypothesis was formulated as follows:

H4: The auditor experience positively and significantly affects forensic audit

Big Data is a collection of large and complex data that requires technology to analyze [32]. It could maximize the forensic audit function to detect fraud through its capabilities and be an answer to overcome agency problems. In detecting fraud, sometimes the auditor has limitations in analyzing unstructured and non-financial data, such as meeting results, news related to management, and contract details. They could overcome these obstacles using Big Data through data analysis tools [33]. Big Data has a large volume and integrated information that could speed up forensic auditors in performing analytical procedures. It increases the auditors' effectiveness and efficiency in detecting fraud.

Furthermore, Big Data could increase the relevance of audit evidence and improve evaluation and audit quality, including forensic audits. An example is when auditors verify shipping information. Forensic auditors could use and maximize GPS data to get more valid information about verifying shipments. Big Data is essential in maximizing forensic audits [33]. According to [25] also found that Big Data positively affects audits. Therefore, the hypothesis was formulated as follows:

H5: Big Data positively and significantly affects forensic audit

Auditors must maintain their independence and a professional attitude when conducting audits to build trust in clients. They must continuously follow developments in their business and profession. More experience increases the auditors' expertise and improves fraud risk assessment skills [34]. Therefore, the hypothesis was formulated as follows:

H6: Forensic audit mediates the effect of auditor experience on fraud detection

A forensic audit is used in fraud detection, whose effectiveness could be increased by Big Data. Combining Big Data and forensic auditing is an effective solution to overcome agency problems [25]. Forensic auditors utilize special investigative skills to reveal various forms of fraud to be proven in the litigation process [10]. Detecting fraud could combine the forensic audit's effectiveness with the use of data [25]. Forensic auditors with proficient expertise improve Big Data's role in facilitating faster, more detailed, and more comprehensive fraud detection [28]. According to [33], fraud detection is effective when combined with Big Data and forensic audits. According to [29], forensic auditing combines disciplines such as law, litigation, criminology, investigation, public sector administration, and information and communication technology in fraud detection. Forensic auditors collect audit and legal evidence with complex criteria that require mastering many competence areas. The assigned auditor must be experienced, astute, and always use professional skepticism to increase the audit's success. By applying skepticism, the auditor pays attention to various nonverbal cues that lead to the expected evidence. [8] and [6] showed that forensic audits effectively detect fraud. Therefore, the hypothesis was formulated as follows:

H7: Forensic audits mediate the effect of Big Data on fraud detection

3. METHODS

This quantitative study used primary and determined respondents using the snowball sampling technique. Respondents comprised internal, external, and government auditors working in

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Indonesia. The data source used in this study is primary data from questionnaires. There are 40 questions divided into four parts. The items were adopted from well-established and published works based on the models. Eight items were taken from [18] and [25] to measure fraud detection. The auditor experience construct was measured through 7 items adopted from [35] and [36]. The eighteen big data constructs were derived from [37]. And the forensic audit construct was measured using seven items adopted from [18]. All item indicators were scored using a four-point, Likert scale, from "1 = strongly disagree" to "4 = strongly agree. The questionnaire was created via a Google form and then shared via social media and group posts from July 8, 2022, to August 12, 2022.

The population size is unknown because there is no valid data regarding Indonesia's current number of external auditors. The Lemeshow formula was used to get the sample.

$$n = \frac{Z_{1-\alpha/2}^{2} \times p(1-p)}{d^{2}}$$

$$= \frac{1.96^{2} \times 0.5(1-0.5)}{(0.1)^{2}}$$

$$= 96.04$$

$$\approx 100$$

From the formula, we obtained a minimum sample of 100 respondents. One hundred twenty-eight respondents completed the questionnaires collected. Testing the validity and dependability of each indicator is the initial step in assessing the model, followed by hypothesis testing. The validity test uses convergent validity, average variance extracted (AVE), and discriminant validity. Reliability tests use composite reliability and Cronbach's Alpha. After completing these stages, we conduct structural model analysis (hypothesis testing). Hypothesis testing observes the P-values and t-tests to determine the relationship between the independent and dependent variables. Data were collected by distributing online questionnaires measured using a Likert scale. The data were analyzed using the structural equation modeling (SEM) approach with SMART Partial Least Square (PLS) software.

4. RESULT AND DISCUSSION

One hundred twenty-eight respondents filled out the questionnaire. Table 2 shows the respondents' demographic details regarding gender, age, domicile, position, education, auditor type, company size, work, and auditor experience.

Table 1: Demographic Factors

Description	N	(%)	Description	N	(%)
Gender			**Education**		
Male	86	67.19	Diploma	3	2.34
Female	42	32.81	Bachelor degree	96	75.00
Age			Postgraduate	29	22.66
21 - 30 years old	70	54.69	Others	0	0.00
31 - 40 years old	34	26.56	**Auditor Type**		
41 - 50 years old	12	9.38	Government Auditor	5	3.91
> 50 years old	12	9.38	Internal Auditor	81	63.28
Domicile			External Auditor	42	32.81
Sumatra	2	1.56	**Company Size Work**		
Java	121	94.53	Small Firm	1	0.78
Borneo	4	3.13	Medium Firm	23	17.97
Sulawesi	1	0.78	Large Firm	104	81.25
Papua	0	0.00	**Auditor Experience**		
Position			< 1 year	17	13.28
Associate Auditor	16	12.50	2 - 5 years	72	56.25
Young Auditor	24	18.75	6 - 10 years	22	17.19
First Auditor	24	18.75	> 10 years	17	13.28
Provider Auditor	0	0.00	**Does your company use Big Data and forensic audits in fraud detection?**		

Advanced Executing Auditor	6	4.69	Yes	128	100.00
Implementing Auditor	18	14.06	No	0	0.00
Audit Manager	15	11.72	**Have you ever carried out fraud detection using Big Data and forensic audits?**		
Partners	3	2.34	Yes	128	100.00
Others	22	17.19	No	0	0.00

Source: Processed by Researcher, 2022

4.1. The Evaluation of the Measurement Model or Outer Model

4.1.1. Convergent Validity

Convergent validity is the loading factor value on the latent variable with its indicators. According to [38], the construct's variance versus the level due to measurement error of more than 0.7 is considered very good. A level of 0.5 and above is acceptable. Table 2 shows the validity test results:

Table 2: Cross Loading

	Auditor Experience	Big Data	Forensic Audit	Fraud Detection
	Forensic Audit (AF)			
AF1			**0.727**	
AF2			**0.807**	
AF3			**0.823**	
AF4			**0.720**	
AF5			**0.762**	
AF6			**0.732**	
	Big Data (BD)			
BD1		**0.778**		
BD2		**0.874**		
BD3		**0.870**		
BD4		**0.883**		
BD5		**0.866**		
BD6		**0.721**		
BD7		**0.753**		
BD8		**0.731**		
BD9		**0.717**		
BD10		**0.855**		
	Auditor Experience (PA)			
PA1	**0.745**			
PA2	**0.824**			
PA3	**0.881**			
PA4	**0.827**			
	Fraud Detection (PF)			
PF1				**0.829**
PF2				**0.896**
PF3				**0.818**

Source: Processed Data

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4.1.2. Discriminant Validity

Discriminant validity is the magnitude of the loading value between aspects or components greater than the value of other aspects or components [39]. It is measured by analyzing the cross-loading between indicators and cross-loading Fornell-Lacker. Table 3 shows that the loading value for the intended construct exceeds the value for other constructs. The Fornell-Lacker's cross-loading value is checked by determining the AVE's root value, which must exceed the correlation between constructs. Table 3 shows the test results:

Table 3: Latent Correlation Variable

	Auditor Experience	Big Data	Forensic Audit	Fraud Detection
Auditor Experience	0.821			
Big Data	0.402	0.808		
Forensic Audit	0.393	0.353	0.763	
Fraud Detection	0.445	0.332	0.421	0.849

Source: Processed Data

The AVE root value in Table 3 exceeds the correlation between constructs. The two-stage cross-loading examination results show no problem in the discriminant validity test.

4.1.3. Construct's Reliability

The reliability of the external construct model measurement with reflective indicators was measured by determining the composite reliability of the indicator block. Table 4 shows the results:

Table 4: Reliability and Validity Constructs

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Auditor Experience	**0.837**	**0.892**	**0.673**
Big Data	**0.941**	**0.949**	**0.652**
Forensic Audit	**0.859**	**0.893**	**0.582**
Fraud Detection	**0.806**	**0.885**	**0.720**

Source: Processed Data

The results in Table 4 show that the overall construct has a relatively high composite reliability value > 0.7. The recommended Cronbach Alpha value is more than 0.6. Therefore, all the variables have a Cronbach Alpha value above 0.6.

4.2. The Evaluation of the Structural Model or Inner Model

4.2.1. Test Coefficient of Determination (R-square)

The structural or inner model was tested to determine the causality relationship between latent variables, the significance, and the R-square values of the study model. The R square value shows the effect of the independent or exogenous variable on the dependent or endogenous variable. Evaluation of the structural model using PLS began with examining the R-squared value of each latent dependent variable. Table 5 shows the R-squared values estimated using SmartPLS:

Table 5: R- Square

	R Square
Forensic Audit	0.200
Fraud Detection	0.281

Source: Processed Data

The results in Table 5 show that the R-square value of the forensic audit variable is 0.200 and the fraud detection variable is 0.281. Auditor experience, Big Data, and forensic audits could explain 20.0% and 28.1% of the forensic audit

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variability and fraud detection, respectively. Variables outside this model explain the rest.

4.2.2. Hypothesis Testing

A t-test was performed with a 95% confidence level and a freedom value of 1.96. Hypotheses were tested for each latent variable in Table 6

Direct hypothesis

Table 6: Bootsrapping Method

	Original Sample (O)	T Statistics (|O/STDEV|)	P Values
Auditor Experience -> Forensic Audit	0.300	3.207	**0.001**
Auditor Experience -> Fraud Detection	0.293	2.877	**0.004**
Big Data -> Forensic Audit	0.232	2.025	**0.043**
Big Data -> Fraud Detection	0.122	1.208	**0.228**
Forensic Audit -> Fraud Detection	0.263	2.759	**0.006**

Source: Processed Data

Indirect hypothesis

Table 7: Bootsrapping Method

	Original Sample (O)	T Statistics (|O/STDEV|)	P Values
Big Data -> Forensic Audit -> Fraud Detection	0.061	1.385	**0.167**
Auditor Experience -> Forensic Audit -> Fraud Detection	0.079	2.012	**0.045**

Source: Processed Data

The results in Table 6 show that seven t-statistic values are less than 1.96 and are insignificant because they are more than 5%. Four t-statistic values are significant or illuminated in green. These results indicate that only four of the seven hypotheses are accepted, and three are rejected. Based on Tables 6 and 7, the first hypothesis shows that the t-count value is 2.877 > t-table of 1.96, and the significance is smaller than the 5% level of distrust, which is 0.004 <0.05. Therefore, the first hypothesis that auditor experience positively and significantly affects fraud detection is accepted.

The second hypothesis shows that the t-count value is 1.208 > t-table of 1.96, and the significance exceeds the 5% level of distrust, which is 0.228 > 0.05. The second hypothesis that Big Data positively and significantly affect fraud detection is rejected. The third hypothesis shows that the t-count value is 2.759 > t-table of 1.96. The significance is smaller than the 5% level of distrust, which is 0.006 <0.05. The results support the third hypothesis that forensic audits positively and significantly affect fraud detection. The fourth hypothesis shows that the t-count value is 3.207 > t-table of 1.96, and the significance is 0.001 <0.05, smaller than the 5% level of distrust. These results support the fourth hypothesis that the auditor's experience positively and significantly affects forensic audits. For the fifth hypothesis, the t-count value is 2.025 > t-table of 1.96, and the significance is 0.043 <0.05, smaller than the 5% level of distrust.

The results support the fifth hypothesis that Big Data positively and significantly affects forensic audits. For the sixth hypothesis, the t-count value is 2.012 > t-table of 1.96. The significance is 0.045 <0.05, smaller than the 5% level of distrust. The results support the sixth hypothesis that auditor experience is more substantial when mediated by forensic audit. For the seventh hypothesis, the t-count value is 1.385 < t-table, which is 1.96. The significance is 0.167> 0.05, more significant than the 5% level of distrust.

Therefore, the seventh hypothesis that forensic audit mediates the effect of Big Data on fraud detection is rejected. The internal or structural model was tested to determine the relationship between the model's construct, significance, and R-square value. Structural models were evaluated using R-square for the t-test dependent construct and the significance of the structural path parameter coefficient.

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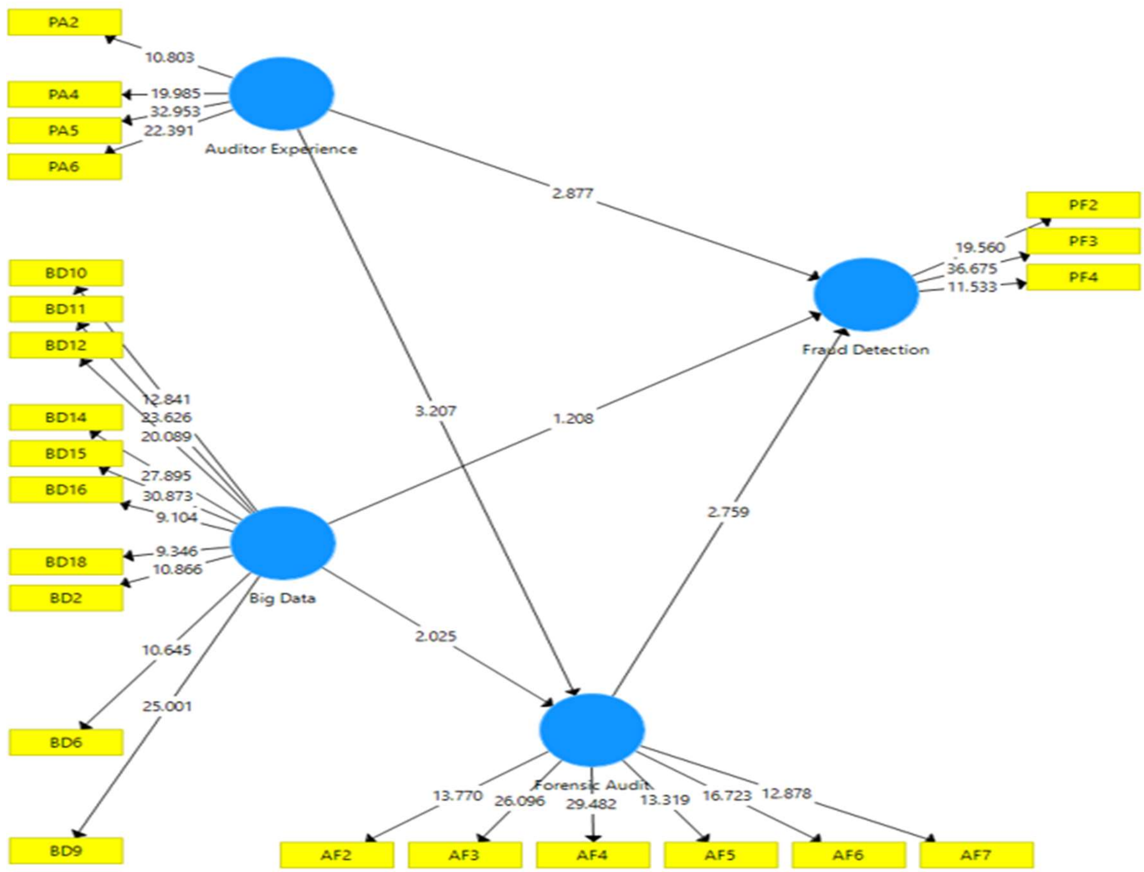

Figure 2: Structural Model
Source: Processed Data

4.2.3. Discussion

This study aimed to examine the effect of auditor experience, Big Data, and forensic audit as mediating variables on fraud detection. The results supported the first hypothesis (H_1) that auditor experience positively and significantly affects fraud detection, as shown in Table 8. Auditors' experience may increase or decrease in detecting fraud depending on the surrounding contextual factors. Higher experience makes auditors more capable and proficient in mastering themselves and the activities being audited. Experience allows auditors to resolve obstacles and control the emotions of those being examined. It is essential to increase the auditor's sense of responsibility to detect fraud. Highly experienced auditors easily detect fraud because the number and types of cases exceed those identified by less experienced auditors. Based on the respondents' demography, most male respondents vote strongly agree with the auditor's experience detecting fraud.

Moreover, younger auditors are more enthusiastic about seeking auditing experience, increasing their proficiency in fraud detection. The results support [40] that the auditors' experience significantly affects their sensitivity to detecting fraud. Characteristics of experienced auditors include skepticism, professional judgment, and acquisition of knowledge about fraud risks in conducting audits. Additionally, the findings support [41], [42] that less experienced auditors have difficulty detecting fraud. It implies that more experienced auditors have a higher ability to take responsibility for detecting fraud. According to [43], experience positively affects the auditor's responsibility in detecting fraud. However, this study contradicts [24] that the auditor's work experience positively but insignificantly influences fraud detection.

The second hypothesis (H_2) states Big Data positively and insignificantly affects fraud detection, was rejected, as shown in Table 6. Big Data is challenging because it has extensive and redundant information. Although tools could help auditors store this information, the data volume increases yearly. Many organizations find it challenging to collect data. Furthermore, the data must be further processed to ensure it is valid and meets clients' needs. The results contradict [27], where 72% of 466 companies participating in the survey stated that Big Data technology is crucial in preventing and detecting fraud.

Moreover, [28] found that Big Data effectively and efficiently detect fraud. Technology development is increasingly rapid, providing many changes, such as the operational activities of various companies today. Many company activities rely heavily on the facilities provided by computers and the internet. The facilities could be speed in data transfer, operation, deletion, or modification [44].

According to [44] explained that these technological advances could also have negative impacts. One such impact is the increasing and complex fraud activity supported by technology. It makes the fraud detection process even more complicated. Therefore, this could be overcome using the same technology. The third hypothesis (H_3) that forensic audit positively and significantly affects fraud detection was accepted, as shown in Table 6. According to [10] explained that a forensic audit comprises special activities to detect and collect legal evidence and facts on fraud cases in the litigation process. However, forensic audits are believed to have two prominent roles. First, they maximize Big Data's role in detecting fraud. Various advantages of Big Data, such as fast data creation, could be maximized by forensic auditors for fraud detection [28], [33], [7]. According to [18], [25] forensic audits effectively detect fraud. Furthermore, [45] showed that proactive and reactive forensic audits significantly negatively impact fraud practices.

The fourth hypothesis (H_4) that auditor experience positively and significantly affects forensic audits was accepted, as indicated in Table 6. Forensic audits need the skills or experience to obtain evidence and present findings and explanations that support administrative, civil, or criminal actions [6]. The audits rely on accounting and auditing knowledge assisted by the ability and experience to conduct investigations [46]. Therefore, a forensic audit could be adapted as an internal audit strategy to prevent fraud. The fifth hypothesis (H_5) that Big Data positively and significantly affects forensic audits was accepted, as shown in Table 8. According to [44], [47], Big Data is a collection of large and diverse information that is difficult to process using traditional approaches. It has five main characteristics, including Volume, Variety, Value, Veracity, and Velocity, abbreviated as 5V. This data assists auditors in analyzing more extensive, diverse, and faster amounts of data, making it easier to identify fraud [48]. Therefore, the Data allows auditors to obtain additional external information from various sources, such as social media, email sites, websites, and online media portals [49]. The data analyzed by auditors using Big Data is very complex and requires a more in-depth analysis process.

The tools contained in Big Data facilitate quick analysis of large amounts of structured and unstructured data. It means that the data is crucial in improving the quality of an audit, including forensic audits. This study also found that Big Data positively affects forensic audits. Therefore, the hypothesis test indicated that using this data for forensic audits in fraud detection solves agency problems. It is in line with [25] that the data positively and significantly affects forensic auditing. The sixth hypothesis (H_6) that auditor experience is more substantial when mediated by the forensic audit was accepted, as shown in Table 7. Forensic audits rely on accounting and auditing knowledge assisted by the ability to conduct investigations [46]. Therefore, a forensic audit could be an internal audit strategy to prevent fraud. Forensic auditors need the skills to obtain and present evidence that supports administrative, civil, or criminal actions [6]. The audits are carried out by utilizing special investigative skills in conducting investigations to provide results with judicial applications. This description indicates a positive relationship between forensic audits and fraud detection. Experience assists auditors in increasing their knowledge of errors and fraud. More experience increases the auditors' expertise and improves their fraud risk assessment ability [34]. Furthermore, experience is an auditor's internal factor that helps understand the flow of detecting fraud. The auditor's success in detecting fraud depends on internal factors. Auditors experienced in fraud assessment are more proficient and faster at detecting fraud. Therefore, the description indicates a positive relationship between experience and fraud detection.

The seventh hypothesis (H_7) was that Big Data is not stronger when mediated by the forensic

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audit. The results in Table 7 show that the hypothesis was rejected, meaning that forensic audits could not mediate the significant effect of the data on fraud detection. Therefore, Big Data mediated through forensic audits cannot resolve the agency theory problems or fraud acts. It could be because the auditor lacks expertise in various fields of science required to conduct this audit. It necessitates routine training and education in investigative science, criminology, ethics, and government administration. The results contradict [8], [45], which showed the effectiveness of this audit in detecting fraud.

The following are the similarities and differences between this study and previous research is [8] "The Effect of Forensic Auditor Skills, Forensic Auditor Techniques, Forensic Auditor Experience, and Technological Readiness on Fraud Detection", the equation are responden is forensic auditors spread all over Indonesia, the primary data collection technique is a survey method, data analysis technique using SEM-PLS., the variable in this study auditor experience and forensic auditor experience partially have a positive and significant effect on fraud detection. While the difference are the sampling technique is incidental sampling and the variables in this study are auditor skills, forensic auditor techniques. Research [25] "Fraud Detection: The Role of Big Data and Forensic Auditing", the equation are this research was conducted using a quantitative approach to the survey method by distributing questionnaires, statistical testing in this study was in the form of structural equation modeling (SEM) with the help of the smartPLS application and the variables in this study are fraud detection, big data and forensic auditing. While the difference are respondents from this study were 221 auditors who worked at the Supreme Audit Board and the Development and Financial Supervisory Agency of the Republic of Indonesia and the variabels in this study is auditor experience. Research [50] "Effect of Forensic Audit on Bank Fraud in Nigeria", the equation is findings indicate that forensic audits help in improved detection and prevention of bank fraud and while the difference is Data were analyzed using ordinary least squares (OLS) regression model.

5. CONCLUSION

This study aimed to examine the influence of auditor experience, Big Data, and forensic auditing as mediating variables on fraud detection. Five of the seven hypotheses tested were accepted, while two were rejected. Therefore, the auditor's experience, Big Data, and forensic audit positively and significantly affect fraud detection. Auditor experience and Big Data also positively and significantly affect forensic audits. A forensic audit mediates the auditor's experience with fraud detection but does not mediate Big Data against fraud detection. The results indicate that internal, external, and government auditors could find a suitable and efficient method to detect fraud in the future. However, this study was conducted during the COVID-19 pandemic, which impacted the distribution of questionnaires and the collection of results. Future studies could add potential variables that strengthen the relationship between forensic audit and fraud detection. Additionally, they could use variables such as investigative audits.

Auditor experience is the ability possessed by an auditor. Big Data is one of the essential things in today's digital era. However, because there is so much data in Big Data, internal auditors need a way to filter this data to find fraud in a company. Forensic auditing is the ability to collect and use structured and unstructured data to prevent, detect, monitor, or investigate errors, fraud, and non-compliance. Where forensic audits as well as with the auditor's experience can utilize Big Data to filter the data needed for analysis. The impact of rapid technological developments has caused many changes to occur, including changes in the audit stages. An internal auditor must not only have adequate knowledge to carry out his duties, but must also have other skills and competencies. future audits require "accounting plus" skills, including an innovative, global, questioning/challenging mindset; leader ability. With auditor experience, including where the auditor understands big data and has forensic audit skills, it is easier to do fraud detection.

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