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Big data and artificial intelligence on fraud detection: the mediating role of fraud awareness

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ABSTRACT

Purpose: This research aims to examine the influence of Big Data and Artificial Intelligence on Fraud Detection and analyze the role of Fraud Awareness as a mediating variable in strengthening these relationships in modern auditing practices.

Methodology/approach: The sample for this research consists of auditors working at Big Four Public Accounting Firms. The sampling method used a purposive sampling technique with a total of 65 respondents. This study uses primary data obtained from respondents' questionnaire responses. The data analysis in this research employs the SmartPLS method using a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach.

Findings: The research results show that Big Data has a positive impact on fraud detection and fraud awareness, whereas Artificial Intelligence has no significant effect on either of these areas. Fraud awareness enhances fraud detection and partially mediates the effect of Big Data, but does not mediate the effect of Artificial Intelligence.

Practical and Theoretical contribution/Originality: This research integrates the Fraud Triangle Theory and the Technology Acceptance Model (TAM) to explain that the effectiveness of audit technology sophistication in fraud detection depends not only on technological capability but also on auditors' fraud awareness.

Research Limitation: This research is limited to a specific group of auditors, which restricts the generalizability of the findings. In addition, this study focuses solely on Big Data and Artificial Intelligence, and therefore does not consider other technological factors that may also influence the effectiveness of fraud detection.

Keywords: Artificial Intelligence; Big Data; Fraud Awareness; Fraud Detection.

INTRODUCTION

Fraud in the financial world has become a serious threat that not only spans countries but also continues to evolve in tandem with technological advances, such as through digital schemes and data manipulation. This phenomenon has intensified in the post-pandemic period, characterized by the increasing complexity of perpetrators' motives and forms of fraud that are becoming increasingly difficult to identify and address conventionally (Mahya et al., 2023). The Association of Certified Fraud Examiners, based on the Key Findings of the 2025 Indonesia Fraud Survey, reports that corruption accounts for the largest share of total fraud-related losses, at 47.6%, followed by financial statement manipulation at 40.2% and asset misappropriation at 12.2% (ACFE, 2025). The high proportion of losses due to corruption and financial statement manipulation indicates that fraud practices are becoming more systematic and structured, thus requiring the implementation of more effective prevention and detection strategies to maintain the stability and credibility of the financial system.

This condition has become evident in several recent fraud cases in Indonesia, such as financial statement manipulation at eFishery and corruption cases at Indofarma, which demonstrate that even as digital technology continues to develop rapidly, traditional audit approaches still face limitations in identifying increasingly complex and covert fraud patterns. In the eFishery case, investigators revealed practices involving the preparation of dual financial statements, manipulation of revenue data, and the presentation of fictitious information that had the potential to mislead external auditors. These findings suggest weak internal control mechanisms and the limitations of conventional audit procedures in detecting systematic, data-driven anomalies (Nefi et al., 2025). Meanwhile, the corruption case at Indofarma highlights problems with governance and internal supervision, particularly related to the abuse of management authority in financial and funding management, which resulted in state losses of Rp371 billion. The revelation of this case, which caused significant financial losses, highlights the failure of supervision and early detection systems for fraud risks, underscoring the need to strengthen more adaptive and technology-based detection mechanisms (Binekasri, 2024).

As the complexity of fraud threats to financial infrastructure increases, traditional fraud detection techniques and mechanisms are considered increasingly irrelevant. Conventional methods, which have a high false positive rate and rely on static, rule-based systems and manual monitoring, tend to be challenging to adapt to evolving fraud strategies and are unable to learn from new data automatically (Bendhi, 2025). This situation has led to a decline in the effectiveness of traditional methods, particularly with the increasing volume of transactions and complexity of fraud patterns. Therefore, companies need to adopt machine learning algorithms in technology-based fraud detection systems that can analyze large-scale transaction data in real-time, enabling them to identify complex fraud patterns more accurately and efficiently than conventional approaches (Vangibhurathachhi, 2025).

In response to the limitations of traditional fraud detection methods, the emergence of artificial intelligence and Big Data offers transformative solutions to address the complexity of fraud in the digital age. Ellahi (2024) explains that artificial intelligence (AI), through the capabilities of machine learning (ML), deep learning (DL), and natural language processing (NLP), can recognize complex patterns and detect anomalies that are often not identified by conventional approaches. Big Data further enhances AI capabilities by enabling the efficient processing and analysis of large and heterogeneous datasets. Companies that generate high

volumes of data from various sources, such as transaction records, customer interactions, social media, and external databases, can leverage Big Data technology to perform real-time data processing, supporting faster and more accurate detection of fraudulent activities. Thus, the adoption of Big Data and AI enables auditors to manage large and complex datasets more effectively, improve analytical capabilities, and support more informed audit decision-making (Ikhsan et al., 2022).

Although the literature suggests that artificial intelligence and Big Data have the potential to enhance the effectiveness of fraud detection, several studies have also highlighted various challenges in their application. Adhikari et al. (2024) highlight the risks of algorithmic bias, the lack of transparency in AI-based decision-making, and issues related to data privacy and system vulnerability. In addition, the use of Big Data often faces obstacles related to data quality and reliability, privacy protection, and the limited number of human resources with adequate technological competence (Shoetan et al., 2024). These conditions suggest that the successful application of AI and Big Data in fraud detection is not solely determined by technological sophistication, but also by the level of user awareness and understanding of the risks and limitations associated with the technology. Prior studies show that higher levels of user awareness and competence improve the effective use of fraud detection technologies (Rekhi & Johri, 2024), (Yuri & Sari, 2022) and (Aziz & Othman, 2021). However, existing research largely examines technological capability and fraud awareness as separate constructs, without explaining the mediating mechanism through which fraud awareness links AI and Big Data to fraud detection effectiveness. The novelty of this study lies in empirically testing fraud awareness as a mediating mechanism, providing a behavior-based explanation of how the effectiveness of AI and Big Data in improving fraud detection performance depends not only on technological capability but also on users' readiness to recognize, anticipate, and respond to fraud risks.

As the complexity and volume of transaction data increase in the digital age, conventional fraud detection approaches are becoming increasingly irrelevant because they struggle to identify dynamic, hidden patterns of fraud. Although Big Data and Artificial Intelligence (AI) offer superior analytical capabilities to improve the accuracy and timeliness of fraud detection, empirical evidence explaining how these technologies operate through behavioral mechanisms, particularly fraud awareness, remains limited. Therefore, this study aims to examine the effect of Big Data and AI on fraud detection with fraud awareness as a mediating variable. The importance of this research lies in its effort to shift the focus from mere technological sophistication to a more comprehensive understanding of the role of behavioral awareness in determining the effectiveness of fraud detection, thereby contributing theoretically to the accounting and auditing literature and providing practical implications for the design of more adaptive and sustainable fraud detection strategies in the digital era.

To explain the behavioral dimension underlying fraud detection and to strengthen the conceptual framework of this study, this research is grounded in the Fraud Triangle Theory introduced by Cressey (1953), posits that fraud occurs due to the interaction of three primary factors: pressure, opportunity, and rationalization. Pressure reflects the financial and non-financial pressures experienced by individuals, and opportunity arises from weaknesses in internal control systems. At the same time, rationalization represents the process of justifying unethical actions committed by fraud perpetrators. In audit practice, this theory serves as a conceptual basis for identifying fraud risk indicators, which are the primary focus in the fraud detection process. The application of the Fraud Triangle Theory also forms the basis for the

implementation of Statement on Auditing Standards (SAS) No. 99, Consideration of Fraud in a Financial Statement Audit, which replaces SAS No. 82 (Harefa et al., 2025).

However, the increasing complexity of transactions and the large volume of data in the modern business environment have rendered the traditional Fraud Triangle-based audit approach increasingly ineffective, unless supported by the use of adequate analytical technology. This condition highlights that the auditor's ability to identify elements of pressure, opportunity, and rationalization is highly dependent on the extent to which supporting technology can be accepted and utilized optimally. Therefore, this study also integrates the Technology Acceptance Model (TAM) as a framework to explain the factors that influence auditors' acceptance of fraud detection support technology. Davis (1989) developed the Technology Acceptance Model (TAM) as an extension of the Theory of Reasoned Action (TRA), emphasizing that two primary constructs, perceived usefulness and perceived ease of use determine individuals' decisions to adopt technology. Perceived usefulness refers to the belief that the use of technology can improve the quality, performance, and productivity of work (Albawwat & Frijat, 2021). While perceived ease of use describes the extent to which auditors believe that technology can be used without requiring excessive physical or cognitive effort (Al-Ateeq et al., 2022).

Several previous studies have demonstrated that the utilization of big data plays a crucial role in enhancing the effectiveness of fraud detection. Natali et al. (2025) demonstrated that big data has a positive and significant impact on fraud detection by enhancing the ability to analyze transactional data in real-time. These findings are supported by Kurniawan & Kurniawati (2024), Bakri et al. (2023), Sembiring & Widuri (2023), Surono (2023), and Zainal (2023), who consistently found that big data can improve the accuracy and efficiency of audits in identifying anomaly patterns and indications of fraud. However, Claudiastuti (2023) reported different results, showing that big data has no significant effect on fraud detection. In contrast, Koreff et al. (2021) highlighted the risks of data misuse and the concentration of power as negative consequences of big data analytics. The inconsistency of these findings indicates that the effectiveness of big data is not universal and largely depends on the context of implementation and human factors.

Similar findings also appear in research related to artificial intelligence (AI). Natali et al. (2025) demonstrate that AI has a positive and significant impact on fraud detection, enhancing the speed, accuracy, and predictive capabilities of audits. Supriadi (2024), Mawlidy et al. (2024), Sholiqah et al. (2023), and Zainal (2023) further reinforced these results by showing that AI can detect complex fraud patterns, reduce false positives, and support fraud risk prediction. On the other hand, research also confirms that auditor fraud awareness has a strong influence on the effectiveness of technology. Sipayung et al. (2023) and Yuri & Sari (2022) show that a high level of fraud awareness improves auditors' ability to interpret the results of technological analysis and detect fraud more accurately. These findings confirm that big data and AI provide optimal results in fraud detection when supported by auditor awareness and behavioral readiness

Big data refers to the processing of large-scale data in real-time to produce reliable information and quickly identify anomalous patterns. Through this capability, big data enables auditors to understand data patterns more comprehensively, allowing them to identify suspicious transactions that are often hidden in traditional systems (Natali et al., 2025). In addition, big data enables data analysis over a more extended period, revealing previously hidden abnormal patterns that can lead to the identification of actual fraud schemes (Gabrielli et al., 2024). However, big data does not automatically improve fraud

detection effectiveness when the system fails to produce relevant and accurate information or when auditors do not utilize the output optimally.

Therefore, this study adopts the Technology Acceptance Model (TAM), which posits that auditors' acceptance of big data analytics depends on their perceived usefulness and perceived ease of use, as these factors influence their intention and actual system usage. In the auditing context, auditors who perceive big data analytics as helpful and easy to use are more likely to apply system outputs in risk assessment and fraud analysis procedures. Furthermore, this study links big data to the Fraud Triangle Theory, which conceptualizes fraud as the result of interactions among pressure, opportunity, and rationalization. Significant data functions as an analytical tool that translates Fraud Triangle elements into measurable indicators of fraud risk, thereby enabling auditors to detect patterns associated with pressure, opportunity, and rationalization more effectively. Consequently, auditors' acceptance and use of big data analytics enhance their ability to identify fraud-related signals embedded in complex data patterns. In line with this framework, empirical findings show that effective big data implementation contributes positively and significantly to improving fraud detection capabilities Natali et al. (2025), Kurniawan & Kurniawati (2024), Bakri et al. (2023), Sembiring & Widuri (2023), Surono (2023), and Zainal (2023), so it can be assumed that the more successful the implementation of big data in the audit process, the higher the effectiveness of fraud detection. From this explanation, the following hypothesis formulation is obtained:

H_1: Big data has a positive effect on fraud detection

Artificial Intelligence (AI) is a computer system that mimics human intelligence in thinking, learning, and making decisions autonomously. AI is capable of processing large amounts of data, detecting anomalies, and providing real-time insights that surpass traditional manual auditing techniques (Suyono et al., 2025). This capability improves the efficiency of audit practices by reducing human error and increasing the accuracy of fraud detection (Albahsh & Al-Anaswah, 2024). However, the effectiveness of AI in supporting fraud detection depends not only on technological sophistication but also on its success as an audit information system that is accepted and used by auditors.

Therefore, this study adopts the Technology Acceptance Model (TAM), which posits that auditors' acceptance of AI in the audit process is influenced by perceived usefulness and perceived ease of use, which in turn drive the level of technology use. In the context of auditing, auditors tend to utilize AI when they perceive the technology as easy to use and capable of enhancing the effectiveness and quality of audit procedures. Optimal utilization of AI enables auditors to identify anomaly patterns, internal control weaknesses, and irregular behavior that represent the elements of pressure, opportunity, and rationalization in the Fraud Triangle Theory. Thus, the acceptance of AI based on TAM plays an important role in supporting a more comprehensive and sustainable fraud detection process. In line with this framework, empirical findings indicate that the successful application of AI significantly contributes to improving fraud detection capabilities (Natali et al., 2025), (Supriadi, 2024), (Mawlidy et al., 2024), (Sholiqah et al., 2023), and (Zainal, 2023). Accordingly, this study hypothesizes that the more successfully organizations implement AI in the audit process, the higher the effectiveness of fraud detection. From this explanation, the following hypothesis formulation is obtained:

H_2: Artificial Intelligence has a positive effect on fraud detection

Big data plays a dual role, not only as an analytical tool for detecting fraud but also as a strategic mechanism for building fraud awareness through broad, transparent, and integrated

information (Gabrielli et al., 2024). Its use enables auditors to recognize patterns of fraudulent behavior and hidden schemes, thereby strengthening auditors' awareness of risks that conventional audit procedures often fail to detect (Gaswira & Meutia, 2024). However, the availability of large amounts of data does not automatically increase risk awareness, as its effectiveness depends on auditors' data literacy, professionalism, and ethical values. Without adequate preparedness, exposure to abundant data may lead to information overload, reducing sensitivity to fraud indicators.

From the perspective of Fraud Triangle Theory, auditor fraud awareness develops in line with the auditor's increasing ability to recognize fraud indicators related to pressure, opportunity, and rationalization. Big data analytics supports this process by providing more comprehensive empirical evidence regarding financial pressure, internal control weaknesses, and unusual behavior patterns that reflect these three elements. However, the availability of large amounts of data does not automatically increase fraud awareness if auditors are unable to interpret the information professionally. Without adequate analytical skills and a skeptical attitude, excessive exposure to data can actually cause information overload and reduce auditors' sensitivity to fraud red flags. Empirical findings support this, showing that auditors significantly utilize big data in the fraud detection process, due to the role of big data technology, various regulatory violations within an organization can be identified more quickly, thereby increasing the effectiveness of supervision and auditor awareness of fraud risk (Pratiwi et al., 2023). From this explanation, the following hypothesis formulation is obtained:

H_3: Big data has a positive effect on fraud awareness

Artificial Intelligence (AI) can be utilized as a strategic tool in fraud detection and prevention within accounting and financial reporting processes due to its capacity to systematically and efficiently process large volumes of data. Through machine learning, AI can identify and prioritize unusual or suspicious transactions, enabling auditors to detect patterns and anomalies that may not be easily detected through traditional audit procedures (Mawlidy et al., 2024). From the perspective of the Fraud Triangle Theory, fraud aware auditors depend on their ability to recognize indicators of pressure, opportunity, and rationalization. AI supports this process by analyzing data to reveal financial pressure, weaknesses in internal controls, and unusual behavior patterns. However, increased fraud awareness does not occur automatically, as the effectiveness of AI depends on the auditor's ability to interpret the analytical results critically. Accordingly, the full potential of AI technologies can be realized only when they are supported by highly competent auditors who possess strong analytical capabilities and adequate digital literacy (Suyono et al., 2025). Consistently, Rashwan & Alhelou (2020) highlight that AI enhances audit quality and efficiency primarily by complementing, rather than replacing, auditors' professional competence in managing audit complexity. From this explanation, the following hypothesis formulation is obtained:

H_4: Artificial intelligence has a positive effect on fraud awareness

Fraud awareness develops through a comprehensive understanding of the characteristics and risks of fraud, which ensures that all parties within an organization recognize their roles and responsibilities in preventing, detecting, and responding to potential fraud risks (Ramadhan, 2022). In the context of modern auditing, the effectiveness of fraud detection depends not only on the sophistication of the technology employed but also on auditors' ability to interpret analytical results based on professionalism and professional skepticism critically. Drawing on Fraud Triangle Theory, auditors develop fraud awareness by understanding fraud indicators related to pressure, opportunity, and rationalization. Auditors with a high

level of fraud awareness can more effectively identify financial pressures, weaknesses in internal control systems, and behavioral patterns that reflect the rationalization of fraudulent acts. This heightened awareness enables auditors to integrate various red flags throughout the audit process, thereby enhancing the overall effectiveness of fraud detection.

Consistent with this argument, empirical evidence shows that higher levels of auditor fraud awareness significantly strengthen an organization's ability to detect and respond to fraud. Aziz & Othman (2021) demonstrates that, based on the Fraud Triangle Theory, fraud awareness has a positive influence on the perceived effectiveness of fraud prevention and detection efforts. Auditors and organizations reflect this awareness through increased attention to internal control and monitoring mechanisms as proactive responses to fraud risk. Furthermore, Yuri & Sari (2022) report high levels of respondent agreement regarding the critical role of internal control systems, audit functions, and reporting mechanisms as primary tools for identifying and preventing fraud. Collectively, these findings confirm that fraud awareness plays a crucial role in enhancing auditors' capacity to identify, assess, and respond to fraud risks more effectively throughout the audit process. From this explanation, the following hypothesis formulation is obtained:

H_5: Fraud awareness has a positive effect on fraud detection

The use of big data in the audit process enables auditors to obtain broader, more integrated, and in-depth information, thereby facilitating the identification of anomalous patterns and indicators of fraud. However, the availability and sophistication of big data do not automatically enhance the effectiveness of fraud detection when auditors lack sufficient understanding and competence in interpreting analytical outputs. Therefore, accountants need to have adequate educational or training backgrounds related to significant data concepts and implementation so that the information produced can be optimally utilized in the fraud detection process (Mardjono et al., 2024).

From the perspective of Fraud Triangle Theory, fraud awareness develops through auditors' understanding of fraud indicators associated with pressure, opportunity, and rationalization. Such awareness constitutes a critical prerequisite in fraud detection, as an inadequate understanding of red flags prevents auditors from effectively leveraging available information to uncover fraudulent activities. Empirical evidence supports this argument, with Aziz & Othman (2021) demonstrating that, based on the Fraud Triangle Theory, fraud awareness has a positive influence on the perceived effectiveness of fraud prevention and detection efforts. Auditors with higher levels of awareness regarding financial fraud risks tend to engage in more proactive fraud detection practices. In this context, the use of big data technology strengthens fraud awareness by providing analytical techniques that support the systematic identification of fraud indicators (Mittal et al., 2021). Accordingly, fraud awareness functions as a mediating mechanism that links the use of big data to the effectiveness of fraud detection. From this explanation, the following hypothesis formulation is obtained:

H_6: Fraud awareness mediates the effect of big data on fraud detection

Artificial intelligence (AI) has revolutionized the approach to auditing by enabling analytical systems that can automatically and continuously process data to identify transactions and behavior patterns that potentially indicate fraud. However, the analytical output generated by AI does not automatically guarantee an increase in the effectiveness of fraud detection if auditors lack the necessary knowledge and skills to understand and critically evaluate the analysis results. This situation requires auditors to adjust their educational background and improve their professional competencies, particularly in the fields of technology and data analysis, so that the use of AI truly adds value to the audit process.

Within the framework of the Fraud Triangle Theory, increased fraud awareness occurs when auditors can link AI analytical results with fraud indicators that reflect the elements of pressure, opportunity, and rationalization. This awareness strengthens auditors' vigilance against fraud risk and encourages more selective and critical use of AI output in audit decision-making. Empirical evidence suggests that fraud awareness has a positive correlation with perceived effectiveness in fraud prevention and detection (Aziz & Othman, 2021). In line with this, Supriadi (2024) emphasizes that AI currently still requires human supervision in the process of interpreting analysis results. AI does not directly improve the effectiveness of fraud detection without the cognitive readiness of auditors. These findings indicate that artificial intelligence does not directly improve the effectiveness of fraud detection without the support of auditors' cognitive readiness. Auditor competence is a key factor in interpreting AI output and integrating it into risk assessments and audit decisions (Suyono et al., 2025). Therefore, fraud awareness acts as a mediating mechanism that bridges the utilization of AI with a substantial improvement in fraud detection capabilities. From this explanation, the following hypothesis formulation is obtained:

H_7: Fraud awareness mediates the effect of artificial intelligence on fraud detection

This study analyzes two variables, namely Big Data and Artificial Intelligence, which are believed to influence the variable of Fraud Detection, and adds the mediating variable of Fraud Awareness. Based on the estimation of these variables, the researcher developed the following research framework:

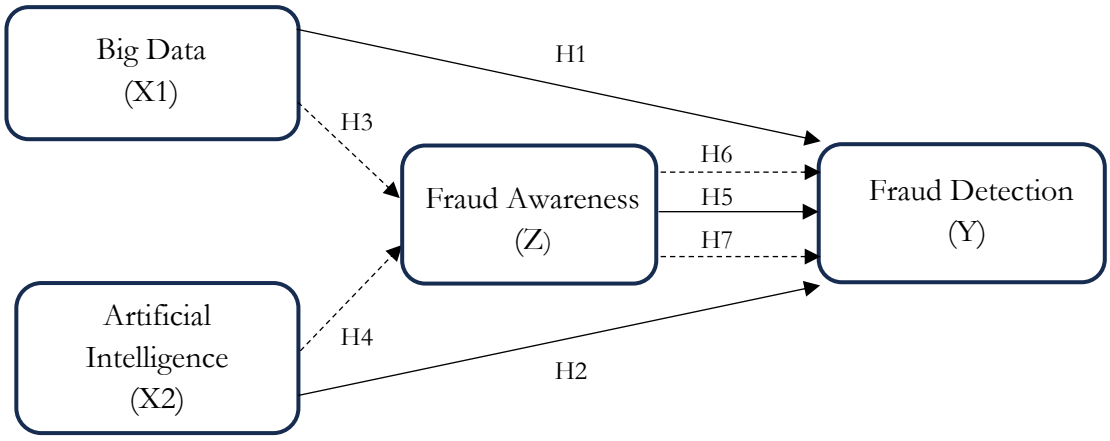

Figure 1. Research Outline

METHOD

This study employs a quantitative approach to empirically investigate the impact of Big Data and Artificial Intelligence on Fraud Detection, with Fraud Awareness serving as a mediating variable. This approach enables the examination of relationships among variables using numerical data analyzed statistically. The study population consists of auditors working at Big Four public accounting firms, which were selected because they have widely adopted big data and artificial intelligence technologies in the audit process, making them highly relevant to the research context. Accordingly, this study applies purposive sampling, a technique that selects respondents based on specific criteria aligned with the research objectives (Sugiyono, 2022).

The determination of the sample size in this study follows the guideline proposed by Hair formula, which states that the minimum sample size in structural equation modeling (SEM)-based research can be determined as 5–10 times the number of indicators used. Based on the total number of indicators employed in this study, the minimum required sample size is calculated as 5 × 10 indicators, resulting in a minimum of 50 respondents. The final sample consisted of 65 respondents who met the predetermined criteria. This study utilizes primary data collected directly from respondents through the distribution of questionnaires. Data were collected using an online questionnaire administered via Google Forms, which was distributed to auditors working at Big Four public accounting firms through the professional networking platform LinkedIn. According to Sugiyono (2022), the Likert scale is commonly used to measure individuals' or groups' attitudes, perceptions, and opinions regarding social phenomena. Accordingly, the research instrument was designed using a five-point Likert scale consisting of: (1) strongly disagree, (2) disagree, (3) neutral, (4) agree, and (5) strongly agree. The use of a five-point Likert scale was chosen because it allows for a more nuanced capture of respondents' perceptions and provides a balanced range of positive and negative response options, thereby enhancing the reliability and sensitivity of attitude measurement.

According to the Association of Certified Fraud Examiners, fraud is an intentional act committed by individuals or groups, either within or outside an organization, to obtain personal or collective gain that has the potential to cause direct or indirect losses to other parties (ACFE, 2022). Meanwhile, fraud detection can be understood as a process of identifying and uncovering various illegal or unlawful acts that harm the parties affected by such acts (Syahputra & Afnan, 2020). The fraud detection indicators in this study were adapted from Natalia & Latrini (2021) which include knowledge about fraud and ability in the detection stage.

Big data refers to a set of data management processes involving massive volumes of data, both structured and unstructured (Pratiwi et al., 2023). Along with the rapid development of digital technology, big data can also be understood as a condition where the amount, speed, and complexity of data evolve in such a way that they exceed the capabilities of conventional information technology systems in managing, storing, and analyzing data effectively (Wildan, 2021). The Big Data indicators in this study refer to the 4V concept proposed by Bandiyono (2023) namely Volume (the size and complexity of data), Variety (the diversity of data types), Velocity (the speed of data processing), while Veracity relates to (the level of accuracy and quality of data).

Artificial intelligence is a field of computer science that focuses on improving systems or machines capable of performing tasks that typically require human intelligence, including the ability to learn, understand natural language, make decisions, and recognize patterns (Fatria et al., 2024). In practice, artificial intelligence technology enables systems to efficiently analyze large amounts of data and generate information that supports the effectiveness of work processes, including those related to auditing and fraud detection. The artificial intelligence indicators in this study were adapted and modified from Albawwat & Frijat (2021) which include perceived ease of use and perceived usefulness in supporting the audit process.

Fraud awareness can be defined as the level of awareness of individuals and organizations regarding the risks and possibilities of fraud, which is reflected in their understanding of various indicators or warning signs (red flags), as well as their vigilance in preventing and detecting fraud at an early stage (Yuri & Sari, 2022). The fraud awareness indicators in this study were adapted from the concept of fraud awareness proposed by Yuri & Sari (2022)

particularly those related to auditors' perceptions and understanding of responsibilities, audit standards, and professional responses to fraud risks. In addition, this study added several development indicators tailored to the context of modern audit technology.

The analytical analysis in this study employs the Partial Least Squares approach with Structural Equation Modeling (SEM) equations to determine the relationship or correlation between the variables under study. This approach was chosen because it has an analytical principle that aligns with multiple linear regression, which enables the simultaneous analysis of the effects of several independent variables on the dependent variable, thereby providing a more comprehensive picture of the relationship. The SEM-PLS method is also powerful and flexible because it does not require the assumption of normal data distribution and is capable of estimating complex models with many latent constructs, indicators, and structural paths (Ghozali, 2022). In the PLS-SEM data analysis technique, there are two main submodels, namely the measurement model (outer model), which includes testing convergent validity and discriminant validity to ensure the validity and reliability of the research instruments, and the structural model (inner model), which is used to test the causal relationships between variables or test hypotheses through a regressive prediction approach. Data processing in this study was conducted using the SmartPLS 4.0 application to facilitate more effective analysis and interpretation of the results.

RESULT AND DISCUSSION

This study is based on the distribution of questionnaires collected through Google Forms as primary data, which were addressed to auditors working at Big Four Public Accounting Firms. A total of 65 respondents were successfully collected and all respondents met the predetermined criteria, so all of them could be used as a research sample in testing the hypothesis. Data analysis was performed using descriptive analysis by explaining and evaluating each respondent's answer, so that general conclusions could be drawn for each research variable. The following are the results of the analysis test:

Characteristic	Information	Sum
Gender	Man	41
	Woman	24
	Sum	**65**
Age	≤ 25 Years	54
	26 – 30 Years	11
	31 – 40 Years	0
	> 40 Years	0
	Sum	**65**
Education Level	D3/D4	1
	S1	64
	S2	0
	Sum	**65**
Work Positions	Junior Auditor	50
	Senior Auditor	10
	Assistant Manager	3
	Manager	2
	Sum	**65**

Work Experience	≤ 2 Years	47
	3 – 5 Tahun	15
	6 – 10 Tahun	3
	> 10 Tahun	0
	Sum	**65**
Have Sertifications	Have	24
	Don't Have	41
	Sum	**65**

Table 1. Characteristics Responden

Source: Output SmartPLS 4, 2026

Name	Average	Median	Scale Min	Scale Max	Standard Deviation
DF1	4.385	4.000	3.000	5.000	0.546
DF2	4.585	5.000	3.000	5.000	0.552
DF3	4.415	4.000	3.000	5.000	0.605
DF4	4.354	4.000	3.000	5.000	0.618
DF5	4.523	5.000	3.000	5.000	0.585
DF6	4.585	5.000	4.000	5.000	0.493
DF7	4.492	5.000	3.000	5.000	0.585
BD1	4.400	5.000	3.000	5.000	0.675
BD2	4.400	4.000	3.000	5.000	0.652
BD3	4.385	4.000	3.000	5.000	0.649
BD4	4.369	4.000	3.000	5.000	0.692
BD5	4.369	4.000	3.000	5.000	0.692
BD6	4.369	4.000	3.000	5.000	0.646
AI1	4.092	4.000	3.000	5.000	0.818
AI2	4.108	4.000	2.000	5.000	0.843
AI3	3.938	4.000	2.000	5.000	0.875
AI4	4.123	4.000	2.000	5.000	0.832
AI5	4.108	4.000	2.000	5.000	0.787
FA1	4.769	5.000	3.000	5.000	0.456
FA2	4.769	5.000	3.000	5.000	0.456
FA3	4.769	5.000	4.000	5.000	0.421
FA4	4.585	5.000	4.000	5.000	0.493
FA5	4.692	5.000	4.000	5.000	0.462

Table 2. Results of Descriptive Analysis

Source: Output SmartPLS 4, 2026

The Fraud Detection (DF) variable, as a result of respondent assessment, ranges from a minimum value of 3.000 to a maximum value of 5.000. The highest average value is found in the DF7 indicator at 4.585 with a median value of 5.000. This average value can be interpreted based on a 1–5 Likert scale, indicating that the respondents' answers fall into the categories of "agree" to "strongly agree". Meanwhile, the standard deviation ranges from 0.493 to 0.618, indicating that the data distribution is relatively small, as the standard

deviation is lower than the average value. Consequently, the respondents' answers tend to be homogeneous.

The Big Data (BD) variable, as assessed by the respondent, has a minimum value of 3,000 and a maximum value of 5,000. The highest average value in the BD1 indicator, with a value of 4,400 and a median of 5,000. This average value indicates that respondents' perceptions of significant data utilization fall within the "agree" to "strongly agree" category. The standard deviation value, which ranges from 0.646 to 0.692, indicates that the variation in respondents' answers is relatively small, suggesting that the data are stable and consistent.

The Artificial Intelligence (AI) variable, based on respondent assessments, ranges from a minimum value of 2.000 to a maximum value of 5.000. The highest average value is found in the AI4 indicator, with a value of 4.123, while the lowest average value is in the AI3 indicator, at 3.938. Based on a Likert scale of 1–5, this average score indicates that respondents' perceptions of the use of artificial intelligence fall into the categories of "disagree" to "agree." The standard deviation values, ranging from 0.787 to 0.875, indicate that the variation in respondents' answers remains within reasonable limits, albeit smaller than the average value.

The Fraud Awareness (FA) variable, as assessed by respondents, ranges from a minimum value of 3.000 to a maximum value of 5.000. The highest average value is in the FA1, FA2, and FA3 indicators, which is 4.769 with a median value of 5.000. This average value indicates that respondents' level of fraud awareness is in the strongly agree category. Meanwhile, the standard deviation value, ranging from 0.421 to 0.493, indicates a minimal level of data dispersion, suggesting that respondents have a highly consistent perception of the importance of fraud awareness.

Variabel	Instruments	Outer Loading	Information
Detection Fraud	DF1	0.829	Valid
	DF2	0.732	Valid
	DF3	0.805	Valid
	DF4	0.882	Valid
	DF5	0.814	Valid
	DF6	0.800	Valid
	DF7	0.756	Valid
Big Data	BD1	0.834	Valid
	BD2	0.849	Valid
	BD3	0.877	Valid
	BD4	0.918	Valid
	BD5	0.863	Valid
	BD6	0.896	Valid
Artificial Intelligence	AI1	0.882	Valid
	AI2	0.832	Valid
	AI3	0.762	Valid
	AI4	0.869	Valid
	AI5	0.797	Valid

Table 3. Results of Convergent Validity Test

Fraud Awareness	FA1	0.845	Valid
	FA2	0.737	Valid
	FA3	0.819	Valid
	FA4	0.760	Valid
	FA5	0.846	Valid

Source: Output SmartPLS 4, 2026

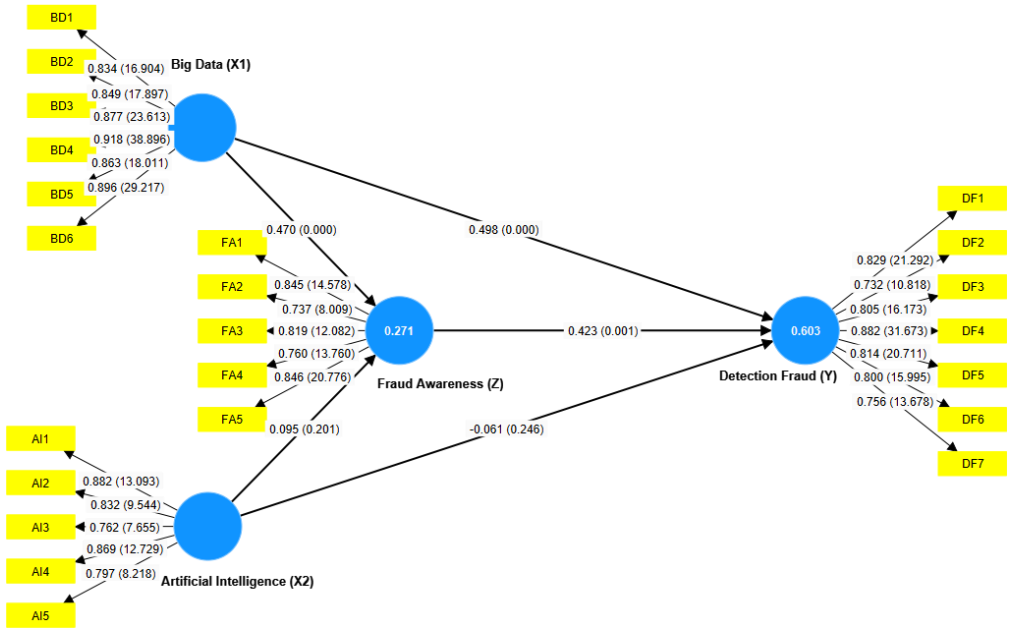

Figure 2. Bootstrapping Test Results

Table 4. AVE Score (Average Variance Extracted)

Variable	AVE Score	Information
Big Data (X1)	0.763	Valid
Artificial Intelligence (X2)	0.688	Valid
Detection Fraud (Y)	0.646	Valid
Fraud Awareness (Z)	0.644	Valid

Source: Output SmartPLS 4, 2026

Convergent validity testing is used to assess the ability of each indicator to represent the latent construct being measured. Convergent validity is evaluated through outer loading values, with a value of > 0.70 as the ideal standard, while a value of > 0.50 is still acceptable in exploratory research (Ghozali, 2023). Based on the test results, all indicators in the variables of Big Data, Artificial Intelligence, Fraud Awareness, and Fraud Detection have outer loading values ranging from 0.732 to 0.918. Thus, all indicators in this study are declared valid and have met the criteria for convergent validity.

Convergent validity was also assessed through the Average Variance Extracted (AVE) value. The test results showed that the AVE values for each variable, namely Big Data (0.763), Artificial Intelligence (0.688), Fraud Detection (0.646), and Fraud Awareness (0.644), were all greater than 0.50. This indicates that each latent construct can explain more than 50% of the variance of its indicators, thus meeting the criteria for convergent validity.

Variable	BD	AI	DF	FA
BD1	0.834	0.501	0.503	0.408
BD2	0.849	0.412	0.602	0.445
BD3	0.877	0.364	0.569	0.443
BD4	0.918	0.423	0.667	0.504
BD5	0.863	0.342	0.610	0.377
BD6	0.896	0.401	0.633	0.503
AI1	0.449	0.882	0.297	0.347
AI2	0.403	0.832	0.210	0.275
AI3	0.364	0.762	0.190	0.226
AI4	0.313	0.869	0.233	0.242
AI5	0.379	0.797	0.305	0.179
DF1	0.521	0.342	0.829	0.556
DF2	0.560	0.134	0.732	0.574
DF3	0.559	0.153	0.805	0.462
DF4	0.591	0.381	0.882	0.530
DF5	0.532	0.206	0.814	0.502
DF6	0.582	0.222	0.800	0.509
DF7	0.508	0.259	0.756	0.568
FA1	0.278	0.219	0.446	0.845
FA2	0.337	0.119	0.391	0.737
FA3	0.329	0.290	0.460	0.819
FA4	0.456	0.276	0.629	0.760
FA5	0.562	0.303	0.624	0.846

Table 5. Cross Loadings Results

Source: Output SmartPLS 4, 2026

Variable	Composite Reliability	Cronbach Alpha	Information
Big Data (X1)	0.951	0.938	Reliable
Artificial Intelligence (X2)	0.917	0.886	Reliable
Detection Fraud (Y)	0.927	0.908	Reliable
Fraud Awareness (Z)	0.900	0.865	Reliable

Table 6. Reliability Test Results

Source: Output SmartPLS 4, 2026

If a variable has a Cronbach's Alpha value > 0.70, it indicates stable and reliable results, although sometimes a slightly lower threshold (such as 0.60) may also be used (Ghozali, 2023). The reliability test results in this study indicate that each variable has a Cronbach's Alpha value > 0.70. Similarly, the composite reliability has a value > 0.70. This indicates that all indicators in this study are reliable in the internal model test.

The internal model test was conducted by looking at the R-squared value. The R-square test results show that the Fraud Detection (Y) variable has an R-square value of 0.603. This means that the Big Data, Artificial Intelligence, and Fraud Awareness variables can explain 60.3% of the variation in the fraud detection variable. In comparison, the remaining 39.7% is attributed to other variables outside the scope of this research model. Meanwhile, the Fraud Awareness (Z) variable has an R-square value of 0.271, which indicates that the Big Data and Artificial Intelligence variables can explain 27.1% of the variation in auditor fraud awareness. In comparison, the remaining 72.9% is influenced by other factors not examined in this study.

Table 7. R-Square Test Results

	R-square	***R-square adjusted***
Fraud Detection (Y)	0.603	0.583
Fraud Awareness (Z)	0.271	0.248

Source: Output SmartPLS 4, 2026

Table 8. Hypothesis Test Results

Information	**Original sampel (O)**	**Average Sample (m)**	**Standard Deviation (STDEV)**	**T-Statstic**	**P-Value**
Big Data → Fraud Detection	0.498	0.505	0.115	4.318	0.000
Artificial Intelligence → Fraud Detection	-0.061	-0.049	0.089	0.688	0.246
Big Data → Fraud Awareness	0.470	0.471	0.106	4.433	0.000
Artificial Intelligence → Fraud Awareness	0.095	0.116	0.113	0.838	0.201
Fraud Awareness → Fraud Detection	0.423	0.413	0.132	3.195	0.001
Big Data → Fraud Awareness → Fraud Detection	0.191	0.144	0.069	2.892	0.002
Artificial Intelligence → Fraud Awareness → Fraud Detection	0.046	0.008	0.050	0.797	0.213

Source: Output SmartPLS 4, 2026

The Big Data affects Fraud Detection

The first hypothesis test (H1) suggests that Big Data has an impact on fraud detection. The test results obtained a t-statistic value of 4.318, which exceeds the critical t-value of 1.96, and a p-value of 0.000, which is below the significance level of 0.05. This finding indicates that the effect of Big Data on fraud detection is statistically significant, with a narrow margin of error, allowing the relationship found to be trusted scientifically. The path coefficient value (original sample) of 0.498 indicates a positive relationship, suggesting that the more effectively Big Data is utilized, the more effective fraud detection will be. This confirms that the ability of Big Data technology to process large and complex datasets is a crucial factor in enhancing the quality of fraud detection. Theoretically, these findings are consistent with the Technology Acceptance Model (TAM), which suggests that the effectiveness of advanced

audit technologies depends on users' perceptions of their usefulness in supporting task performance. Big Data analytics enhances auditors' ability to process large and complex datasets more accurately and efficiently, thereby encouraging more intensive and meaningful use in fraud detection. Furthermore, these results align with the Fraud Triangle Theory, particularly the opportunity element, as the application of Big Data increases transparency and strengthens monitoring mechanisms, which in turn reduce opportunities for fraud by enabling the early identification of anomalous and suspicious patterns that are difficult to detect through conventional audit approaches.

Thus, it can be concluded that Big Data has a positive and significant effect on fraud detection, thereby accepting hypothesis (H1). These findings support the theoretical basis that data-driven analytical technology can enhance an organization's ability to identify risks and indicators of fraud more effectively and comprehensively. The results of this study align with those of Natali et al. (2025), which demonstrate that the application of Big Data has a positive impact on fraud detection, particularly in helping auditors understand data patterns more comprehensively, thereby facilitating the identification of suspicious transactions that are often concealed in traditional systems. These findings are also supported by research by Kurniawan & Kurniawati (2024), Bakri et al. (2023), Sembiring & Widuri (2023), Surono (2023), and Zainal (2023), which consistently conclude that Big Data has a positive effect on fraud detection.

The Artificial Intelligence affects Fraud Detection

The results of the second hypothesis (H2) testing show that Artificial Intelligence (AI) does not have a significant effect on fraud detection. This is indicated by a t-statistic value of 0.688, which is smaller than the critical t-value of 1.96, and a p-value of 0.246, which exceeds the significance level of 0.05. In addition, the path coefficient value (original sample) of −0.061 indicates a negative relationship, so the statistical hypothesis H2 is rejected. These findings suggest that the use of AI in this context has not directly enhanced the effectiveness of fraud detection. Theoretically, these findings can be explained through the Technology Acceptance Model (TAM), which indicates that the effectiveness of AI depends on the extent to which it is perceived as useful and meaningfully integrated into audit practices. Limited understanding, low levels of adoption, and suboptimal integration of AI within audit and supervision processes may weaken its perceived usefulness, thereby reducing its practical impact. From the perspective of the Fraud Triangle Theory, AI is expected to constrain the opportunity element by strengthening monitoring and algorithm-based analysis.

However, the results of this study suggest that, in the absence of organizational readiness, high-quality data, and active user awareness and involvement, AI has yet to effectively narrow opportunities for fraud. This condition aligns with Jaiswal & Singh (2025) view that the implementation of artificial intelligence in fraud detection still faces various limitations, particularly related to the low interpretability of models and the need for ethical and transparent governance of AI. Research by Papasavva et al. (2025) and Faisal et al. (2024) also revealed that the application of artificial intelligence has not been optimal due to limitations in model interpretability, data quality, the risk of algorithmic bias, and low transparency in decision-making. The success of AI implementation is not only determined by technical sophistication but also by compliance with regulations, data privacy protection, and user trust levels. Therefore, AI cannot yet fully replace the role of human supervision and is more appropriately positioned as a supporting tool in fraud prevention and detection strategies, rather than as a stand-alone solution.

The Big Data affects Fraud Awareness

The results of testing the third hypothesis (H3) show that Big Data has a positive and significant effect on fraud awareness, as indicated by a t-statistic value of 4.433 (> 1.96) and a p-value of 0.000 (< 0.05). The path coefficient value (original sample) of 0.470 indicates that the use of Big Data directly increases the level of awareness of fraud. This finding confirms that Big Data not only functions as a technical analysis tool but also plays a role in shaping individual awareness of fraud risk, so hypothesis H3 is accepted. Critically, Big Data increases fraud awareness by providing pattern-based information and empirical evidence that clarifies the characteristics of fraud, thereby reducing reliance on intuition alone. From the perspective of the Technology Acceptance Model (TAM), this condition indicates a high perceived usefulness of Big Data, as the technology enables users to understand fraud risks more accurately and in context. Furthermore, by displaying anomalies and risky transaction patterns, Big Data helps reveal the opportunity element as described in the Fraud Triangle Theory, thereby increasing awareness of potential fraud.

Aligns with Pratiwi et al. (2023), who note that the use of Big Data enables the identification of regulatory violations more quickly, thereby enhancing the effectiveness of supervision and increasing auditors' awareness of fraud risks. Literature by Gabrielli et al. (2024) and Rosnidah et al. (2022) also shows that big data can enhance auditors' understanding of fraud indicators and strengthen vigilance during the audit process. Big data not only increases the effectiveness of fraud detection but also encourages greater awareness of fraud among auditors. Therefore, big data functions as a cognitive and structural mechanism that strengthens awareness of fraud and contributes to fraud prevention from an early stage.

The Artificial Intelligence affects Fraud Awareness

The results of the fourth hypothesis (H4) testing show that Artificial Intelligence (AI) does not have a significant effect on fraud awareness. The test results obtained a t-statistic value of 0.838, which is smaller than the critical t-value of 1.96, and the p-value of 0.201, which exceeds the significance level of 0.05. Although the path coefficient indicates a positive relationship of 0.095, the effect is not statistically significant, so hypothesis H4 is rejected. This finding suggests that the presence of AI does not automatically enhance auditors' fraud awareness. From the perspective of the Technology Acceptance Model (TAM), these results indicate that AI is not yet fully perceived as having relevant uses in building awareness of fraud risk, particularly when auditors act as passive users who only receive system output without engaging in deep cognitive involvement. Furthermore, within the framework of the Fraud Triangle Theory, although AI has the potential to help identify the opportunity element, the limitations of model interpretability cause AI to function as a black box system that does not encourage the process of learning or internalizing fraud indicators.

This condition is reinforced by previous findings, which state that some accounting professionals still feel uncomfortable or concerned about the impact of AI implementation, resulting in its slow adoption (Hanetseder et al., 2021). Other literature Murikah et al. (2024) and Banţa et al. (2022) indicates that the lack of transparency in AI systems has the potential to encourage excessive dependence that weakens the skepticism of professional auditors. The adoption of AI risks encouraging auditors to over-rely on system outputs, thereby reducing professional skepticism (Kokina et al., 2025). This decline in skepticism has implications for weakening auditors' fraud awareness. This condition is exacerbated by limited understanding and skills in the use of AI, which hinders the integration of this technology into audit practices. Therefore, AI plays a more significant role as a technical

support tool in the audit process, rather than as a mechanism that directly shapes fraud awareness.

The Fraud Awareness affects Fraud Detection

The results of testing the fifth hypothesis (H5) show that fraud awareness has a positive and significant effect on fraud detection, as indicated by a t-statistic value of 3.624 (> 1.96) and a p-value of 0.000 (< 0.05). The path coefficient value (original sample) of 0.412 indicates that an increase in fraud awareness significantly strengthens the effectiveness of fraud detection, so hypothesis H5 is accepted. Critically, this finding confirms that the effectiveness of fraud detection does not only depend on the existence of audit systems or procedures, but on the cognitive capacity of individuals to recognize and interpret fraud risk indicators. Within the framework of the Fraud Triangle Theory, fraud awareness enables auditors to understand the interrelationship between pressure, opportunity, and rationalization, which are often not explicitly apparent in financial data.

When awareness levels are low, indications of fraud may be perceived as normal anomalies, leaving the door open for fraud to occur. Therefore, fraud awareness serves as a fundamental prerequisite that explains why the fraud detection process can be effective and targeted. The results of this study are in line with Abdul Aziz & Othman (2021) who found that fraud awareness has a positive and significant effect on the effectiveness of fraud detection. The study shows that auditors with a high level of fraud awareness tend to be better prepared in terms of knowledge and skills in recognizing red flags and carrying out effective fraud detection measures. These findings are reinforced by research by Sipayung et al. (2023) and Yuri & Sari (2022) which shows that high fraud awareness improves auditors' ability to recognize indications and symptoms of fraud and encourages the use of various fraud detection methods.

Fraud awareness can mediate the relationship between the influence of Big Data on Fraud Detection

The results of the sixth hypothesis (H6) testing show that fraud awareness mediates the effect of Big Data on fraud detection, as evidenced by the indirect effect coefficient value of 0.191 with a t-statistic of 2.892 and a p-value of 0.002, which is significant at a 95% confidence level. This finding indicates that the effect of Big Data on fraud detection is not only direct but also reinforced through increased fraud awareness as a mediating mechanism, so hypothesis H6 is accepted. Critically, these results confirm that the effectiveness of Big Data in detecting fraud is not solely determined by technological sophistication but rather depends heavily on individuals' ability to understand and interpret the analytical information produced. Theoretically, these findings are consistent with the Fraud Triangle Theory, which posits that Big Data supports fraud detection by revealing patterns related to the opportunity element. However, fraud awareness determines whether auditors interpret these analytical insights as meaningful fraud risk indicators, as insufficient awareness may lead them to perceive Big Data outputs as routine technical anomalies. In line with the Technology Acceptance Model (TAM), the results further indicate that technology acceptance alone is insufficient to enhance fraud detection without the presence of fraud awareness.

Research by Mittal et al. (2021) indicates that auditors with a high level of risk awareness tend to use big data analysis more proactively to identify fraud indicators. This finding aligns with Dewi et al. (2025) which states that auditors who are highly competent in utilizing big data and have a strong level of confidence will be better able to detect fraud accurately and efficiently. The use of big data offers auditors new opportunities to identify potential risks, uncover operational inefficiencies, and generate more comprehensive insights during the

audit process (Rosnidah et al., 2022). Thus, big data plays a clear, strategic role in continuously improving the effectiveness of fraud detection. Therefore, fraud awareness serves as a cognitive mechanism that leverages the role of Big Data in reducing opportunities for fraud, making the integration between technology and individual awareness the key to enhancing the effectiveness of fraud detection.

Fraud awareness can mediate the relationship between the influence of Artificial Intelligence on Fraud Detection

The results of testing the seventh hypothesis (H7) show that fraud awareness does not mediate the effect of Artificial Intelligence (AI) on fraud detection, as indicated by an indirect effect coefficient value of 0.046 with a t-statistic of 0.797 and a p-value of 0.213, which exceeds the 0.05 significance level. This finding indicates that the influence of AI on fraud detection is not transmitted through fraud awareness as a mediating mechanism. Therefore, hypothesis H7 is rejected. Critically, the insignificant mediating role of fraud awareness suggests that the use of AI has not been fully effective in shaping fraud awareness among auditors. Within the framework of the Fraud Triangle Theory, AI should help identify opportunities through automatic and predictive analysis. However, the complex and opaque (black box) characteristics of AI output make it difficult for auditors to interpret fraud risk indicators cognitively. From the perspective of the Technology Acceptance Model (TAM), this condition reflects the low perceived usefulness and perceived ease of use of AI in building user understanding and awareness.

The literature shows that some accounting professionals remain uncomfortable and concerned about the impact of implementing artificial intelligence (AI), leading to delayed or limited adoption (Hanetseder et al., 2021). This finding aligns with Yaseen & Al-Amarneh (2025) who states that auditors remain cautious in using AI for fraud detection due to the limited transparency and explainability of the system, so that AI output is not yet fully trusted without professional judgment and critical skepticism. These findings are reinforced by Naseer & Ahmed (2025) who show that the limited transparency and explainability of AI systems make it difficult for auditors to understand the basis for fraud detection decisions. This condition has the potential to shift the role of auditors towards accepting system output, thereby weakening their ability to recognize and interpret indications of fraud. Thus, fraud awareness has not yet functioned as an effective mediating mechanism in the relationship between Artificial Intelligence and fraud detection, because the use of AI operates more as a technological detection system than as a trigger for increasing auditors' cognitive awareness.

CONCLUSION

The findings indicate that technological sophistication alone is insufficient to ensure effective fraud detection in modern auditing. Instead, effectiveness depends on the extent to which big data technologies integrate into auditors' cognitive and professional processes, enhancing analytical coverage, anomaly detection, and fraud risk awareness, which ultimately strengthens risk-based auditing and professional skepticism. Conversely, artificial intelligence has not yet optimally contributed to improving fraud detection or fraud awareness, which indicates that advanced analytical technology does not automatically replace the role of professional auditor judgment. These findings confirm that the strategic value of audit technology depends on the auditor's ability to critically and ethically interpret, evaluate, and use system output.

These findings theoretically reinforce the information systems success framework and behavioral approaches by highlighting that audit technologies deliver tangible benefits only

when auditors meaningfully integrate them into practice. However, this study has several limitations. First, the study's scope is limited to auditors working at Big Four Public Accounting Firms in Indonesia, limiting the generalizability of the findings to non-Big Four audit firms. Second, this study focuses solely on the use of Big Data and Artificial Intelligence technologies, thereby omitting other technologies that may also affect fraud detection effectiveness. In light of these limitations, future research should examine a broader range of organizational and jurisdictional contexts, adopt a mixed-methods approach, and consider moderating variables such as technological competence, organizational culture, and ethical climate to deepen our understanding of the relationship between digital technology and auditor judgment in fraud detection.

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