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Big Data, CAATs, and Auditor Religiosity in Fraud Detection: Task-Specific Knowledge as Moderator

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ABSTRACT

Purpose : With task-specific knowledge taken into account as a moderating factor, this study attempts to investigate the impact of big data, computer-asisted audit techniques (CAATs), and auditor religiosity on fraud detection. The growing need for insight into the behavioral and technological components that support efficient fraud detection in audit procedures served as the basis for the study.
Method : Using an associative quantitative approach, the study was carried out at the State Development Audit Agency's Representative Offices in Sumatra. A straightforward random sample method was used to gather data, and 220 questionnaires were filled out. Structural Equation Modeling (SEM) was used in the investigation to determine the correlations between the variables.
Findings : According to the t-test results, auditor religiosity significantly improves fraud detection. Big data and CAATs, however, did not demonstrate a statistically significant impact. Moreover, task-specific information serves as a predictive modifiers rather than a moderating variable as first proposed. With a termination value of 0.974, the model had a very small effect size.
Novelty : The study is innovative since it examines behavioral, technical, and cognitive aspects of the auditing profession in a comprehensive manner. Additionally, it offers fresh perspective by reframing task-specific knowledge as a predicting component rather than a moderating variable, with important ramifications for enhancing fraud detection techniques.

INTRODUCTION

Maintaining financial and operational integrity in the face of increasingly complicated administrative and economic circumstances is a major problem for government institutions in the modern, globalized world. The need for effective budget management, accountability, and transparency has become a central focus. A strong financial system and sound managerial practices are crucial in preventing fraud, particularly during times of financial instability. Fraud detection involves detecting preliminary clues or symptoms of fraud, thus reducing the likelihood of wrongdoing Kumaat (2011), the advancement of Big Data analytics has introduced new methods for enhancing forensic audits and fraud detection Govinand et al., (2018) Computer-Assisted Audit Tools (CAATs) further assist auditors by improving efficiency and effectiveness in data analysis Lin & Wang (2011). Additionally, auditors' ethical integrity, reinforced by religiosity Glock & Stark (1965), and their expertise in audit-related knowledge Libby (1995) contribute to fraud detection capabilities.

Earlier research by Handoko et al. (2022), Syahputra & Afnan (2020), Surono (2023), and Bandiyono (2023) has proved how fraud detection is impacted by big data. However, an investigation conducted by Sembiring & Widuri (2023) produced disparate findings, suggesting that fraud detection is unaffected by big data. Results from Olasanmi (2013), Atmaja (2016), Fauzi et al. (2020), and Samagaio & Diogo (2022) confirm that fraud detection is significantly impacted by CAATs. Research by Widuri & Gautama (2020) found that the application of CAATs is essential, helps uncover fraud, and contributes to the audit process, as evidenced by the application of a qualitative approach.

The implementation of Computer-Assisted Audit Tools (CAATs) by auditors, along with leveraging Big Data

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to enhance forensic auditing in detecting fraud, can optimize both the effectiveness and efficiency of the auditing process. This enables auditors to assess and interpret data more swiftly and accurately. Upholding integrity in auditing becomes more manageable when auditors incorporate religious values into the fraud detection process.

Moreover, task-specific knowledge significantly moderates the influence of the independent variables. Firstly, possessing task-specific knowledge allows auditors to select and apply appropriate data analysis methods and algorithms within the context of fraud detection. This contributes to maximizing the utilization of Big Data in recognizing patterns and anomalies indicative of fraudulent activities. Secondly, auditors with task-specific expertise can more effectively utilize CAATs for detecting fraud. This includes a comprehensive understanding of how to operate data analysis tools and techniques to identify fraudulent indicators within transactions and financial records.

Finally, auditors equipped with task-specific knowledge generally have a deeper comprehension of fraud indicators and effective detection strategies. When combined with auditor religiosity, this knowledge increases their likelihood of conducting audits with a meticulous and detail-focused approach while also heightening their awareness of potential fraud indicators that may emerge during the audit process.

Venkatesh et al. (2003) created the Unified Theory of Acceptance and Use of Technology, which holds that four primary factors—performance expectancy, effort expectancy, social Impact, and enabling conditions—have an impact on how people use technology. By comprehending the elements that affect technology adoption, this theory provides an understanding of how information technology can assist auditors in identifying fraudulent activities. The idea behind cognitive dissonance theory was suggested by Festinger (1957), establishes a vital basis for comprehending social Impact and communication dynamics. This hypothesis draws attention to the cognitive components' inconsistencies, which cause psychological discomfort. Muzdalifah & Syamsu (2020) emphasize how the cognitive dissonance theory affects how auditors' attitudes alter to forecast intentions in an effort to lessen the resulting dissonance or discrepancy. These cognitive elements help auditors make sure that their conclusions following an audit are consistent with the information they find throughout the investigation. According to this hypothesis, people often look for consistency in their attitudes, behaviors, and beliefs. When these elements are inconsistent, cognitive dissonance results, which causes psychological discomfort. Therefore, this hypothesis sheds light on how task-specific knowledge may affect auditors' fraud detection procedures.

Attribution theory was suggested by Heider (1958), focuses on how people justify the reasons for actions and occurrences. Refers to Fiske & Taylor (1991), this theory explores how occurrences may be causally explained through social perception. It is predicated on the idea that people frequently assign dispositional and situational attributions, which are reasons for internal or external variables, in order to explain behavior, whether it be their own or that of others. As a result, this idea sheds light on how auditor religiosity may affect the process of detecting fraud. Religious values are dispositional attributions that will impact auditors' interpretations of suspicious behavior.

Refers to Betri (2022), Fraud is described as an illegal conduct that can be carried out by people inside or outside of an organization for the purpose of gaining personal or collective advantage, which eventually causes direct losses to other people. Organizations may turn to criminal activity in an attempt to improve performance and reputation, ignoring the repercussions and parties involved. Detection, as per the KBBI Daring (2016), describes the endeavor to find and ascertain facts, hypotheses, or the existence of something. Karyono (2013) The process of determining Fraud detection is the process of identifying instances of fraud, its perpetrators, victims, and the reasons behind them.

Big Data is distinguished by its diverse and intricate architecture, which enhances forensic audits and fraud detection by improving data coverage and analytical processes Sağiroğlu & Sinanc (2013). A large collection of data with intricate and diverse structures is referred to as "big data." This strengthens internal auditors' ability to detect fraudulent activities, ultimately improving audit quality Govinand et al. (2018). And it aids companies in identifying fraud risks Bandiyono (2023). CAATs utilize technology and specialized software to enhance audit efficiency, performance, and fraud detection (Lin & Wang, 2011 and Braun & Davis, 2003). Manual testing is not practical in computerized accounting information systems environments, according to Auditing Standard Section 327 for auditors.

Religiosity, defined as an individual's understanding and commitment to religious practices, impacts ethical behavior and fraud detection (Glock & Stark, 1965 ; Sari et al., 2012) religiosity fosters strong moral standards and work ethics, enhancing auditors' independence and commitment to truth and justice (Ghufron & Risnawati, 2012 and Afriana, 2019) Specific Knowledge comprises stored experiences, facts, and theoretical concepts, aiding auditors in planning and executing audits effectively (Libby, 1995 and Sari, 2019). It improves assessment quality and fraud detection by enhancing auditors' understanding of audit environments (Moyes & Hasan, 1996).

According to Chen & Zhang (2014), Big Data is represented as large, complex data that requires cutting-edge technology for analysis. The capability of Big Data to analyze data comprehensively allows for information extraction from large and complex datasets. Govinand et al., (2018) Demonstrate how Big Data may improve forensic auditing's ability to identify fraud. Prior investigation by Syahputra (2020), Handoko., (2022), Bandiyono (2023), and Surono (2023) have shown that big data has a significant influence on fraud detection. However, the findings of the study Sembiring & Widuri (2023) show that fraud detection is not much impacted by huge data. However, organizations that use big data are often better at spotting fraud because they help internal auditors cover more important data sources. The researcher makes the following hypothesis:

H_{1a}: Fraud detection is significantly impacted by big data

CAATs, according to Peranda (2020), are methods that use computers and related technologies to make auditing procedures easier. Zamzami et al. (2021). For automating and auditing audit data, CAATs are crucial tools. In the era of information technology, the paradigm of auditing techniques for fraud detection has changed due to the usage of CAATs. By using CAATs, auditors may examine data more thoroughly, look for suspicious patterns and trends, and identify fraud indications that are hard to spot by hand. According to studies by Olasanmi (2013), Atmaja (2016), Fauzi et.al (2020), and Samagaio & Diogo (2022), Fraud detection is greatly impacted by CAATs. The use of CAATs is essential to the audit process and improves audit results in terms of fraud identification, as demonstrated by this study, which takes a qualitative approach and is backed by research by Widuri & Gautama (2020). However, studies by Choirunnisa & Rufaedah (2022) and Kamal (2022) show that information technology utilization has no effect on auditors' capacity to identify fraud. Consequently, auditors will find it simpler to spot current irregularities if they use CAATs as audit process tools, which will raise the standard of their inspections. The researcher makes the following hypothesis:

H_{1b}: Fraud detection is significantly impacted by computer-assisted auditing techniques

Relates to Glock & Stark (1965), A person's degree of religious conception and amount of devotion to religious practice are indicators of their religiosity. The level of dedication is correlated with a thorough comprehension of religious life, whereas Sari et al. (2012) elucidate the relationship between the idea of conception and a person's comprehension of the elements of their religion. The ability of auditors to detect fraud is impacted by religion, according to a study by Fadilah et al. (2020) and Bandiyono (2023). These results are consistent with research by Suci et al. (2022) that shows that auditors' level of religiosity has a substantial impact on their capacity to detect fraud. Nevertheless, the results of other studies differed from those mentioned above, including the one conducted by Afriana (2019) This proves that religious convictions have no impact on an internal auditor's capacity to spot fraud. The researcher makes the following hypothesis:

H_{1c}: Detection of fraud is significant to impacted by the religiosity of the auditor

Sağiroğlu & Sinanc (2013) Define big data as a vast collection of data that is unique in its complexity, diversity, and reach. Hipgrave (2013) highlights how Big Data may be used to integrate data and speed up fraud investigations. In contrast, Bonner (1990) explains how Task Specific Knowledge has been found to be a critical component of audit execution in his investigation. Decisions made by auditors throughout the audit evaluation process may be influenced by task-specific knowledge. This study indicates that experienced auditors possessing task-specific knowledge tend to exhibit superior performance in assessing the risk of analytical procedures. Both Big Data and task-specific knowledge Impact the fraud detection process. Task-specific knowledge can aid in selecting and implementing algorithms and data analysis methods appropriate to the fraud detection context. This makes it easier to maximize the use of big data to find trends and irregularities that might be signs of fraud. Investigations by Yusrianti (2015), Kusumawaty & Betri (2019), Lembayung & Chomsatu (2021) shows how Task Specific Knowledge has a big influence on auditors' ability to detect fraud. This study is corroborated by research done by Johnson et al., (1993), Tirta & Sholihin (2004), Sari (2019), and Muzdalifah & Syamsu (2020) An investigation demonstrates how auditors' capacity to identify fraud is impacted by task-specific knowledge. Task-specific knowledge helps auditors better understand and complete audit tasks, which improves the quality of their assessments. It also helps auditors discover fraud during the audit process, allowing for more organized planning and execution of audit processes. The researcher makes the following hypothesis:

H_{2a}: The impact of big data on detection of fraud is modified by task specific knowledge

To improve the efficacy and efficiency of the audit process, the use of CAATs has become essential. Braun & Davis (2003) explain how the use of specialized technology by CAATs enhances the audit process and allows auditors to accomplish audit goals. refers to Zamzami et al. (2021), When it comes to automating and auditing audit data, CAATs are crucial. In contrast to Sari (2019) claims that Task Specific Knowledge facilitates organized planning and execution of audit processes by helping auditors comprehend the examined environment and internal situations. Task-specific knowledge helps auditors do tasks more efficiently throughout the audit, which improves the caliber of their evaluations. Encouraged by Bonner (1990), according to his research, auditors' expertise influences the choices they make during the audit evaluation process. Task-specific knowledge and CAATs both have an effect on the fraud detection procedure. Task-specific knowledge helps auditors understand how to use CAATs for fraud detection in the best possible way. This includes having a thorough grasp of how to use tools and data analysis methods to find fraud signs in transactions and records. Investigation by Yusrianti (2015), Kusumawaty & Betri (2019), and Lembayung & Chomsatu (2021) shows that auditors' ability to detect fraud is impacted by task-specific knowledge. This investigation is encouraged by Johnson et al. (1993), Tirta & Sholihin (2004), Sari (2019),

Table 1. Operationalization of Variables

Variable	Definition	Dimension
Fraud detection (Y)	Fraud detection is defined as the process or effort to find and determine indications, early clues, or signs associated with fraudulent acts and identify perpetrators, victims, and motives for fraud.	1. Ability to detect fraud. 2. Have a high vigilance attitude. 3. Have accuracy. 4. Have accuracy.
Big Data (X_1)	Big Data is a large-scale data set with challenging structural complexity in terms of storage, analysis, and visualization, which cannot be accommodated with conventional software. These data sources involve online transactions, social media platforms, and video content.	1. Volume (large size dimension). 2. Variety (variety of data types). 3. Velocity (speed of data creation). 4. Veracity (uncertainty regarding accuracy and reliability). 5. Value (has a high value when processed with the right method).
Computer Assisted Audit Techniques (X_2)	CAATs are the use of various technologies that help auditors perform control testing, confirmation, analysis, verification of financial statement data, and ongoing auditing and oversight of computerized accounting information systems.	1. The need to use CAATs (Perceived Usefulness). 2. Easeness CAATs (Perceived Ease of Use). 3. Attitude Toward Using 4. Acceptance of CAATs.
Religiosity Auditor (X_3)	Religiosity reflects a person's interest, appreciation, and practice of religious teachings, including beliefs, attitudes, and behavior in relationships with nature, vertical relationships (with God), and horizontal relationships (with fellow humans).	1. High level of implementation of religious values in daily life. 2. Active involvement in religious activities. 3. Level of trust in religious leaders.
Task Specific Knowledge (Z)	Task Specific Knowledge involves information in the auditor's memory related to audit performance, including practical experience and audit concepts that require auditor judgment through general and specialized knowledge, assisting in understanding the internal audit environment and conditions.	1. Knowledge 2. Auditor capacity in their assessment of fraud.

Source: Processed of Primary Data, 2024

and Muzdalifah & Syamsu (2020). The Investigation shows how auditors' capacity to identify fraud is impacted by task-specific knowledge. The researcher makes the following hypothesis:

H_{2b}: The impact of CAATs on detection of fraud is moderated by task specific knowledge

The definition of religiousity by Lestari & Indrawati (2017), represents the internalization of religious ideals via understanding and obedience to religious teachings, which is shown in day-to-day actions. Afriana (2019) explains how an auditor's independence may be improved by their level of religion. This is explained by the tendency of very religious people to emphasize justice or righteousness and to resolutely preserve the truth. In contrast with Task Specific Knowledge, as explained by Sari (2019) and Libby (1995), refers to specialist knowledge of certain duties, particularly in the audit sector. This information helps auditors plan and carry out more focused audit processes by helping them understand the internal circumstances and environment of the examined business. The technique of detecting fraud is affected by the auditor's religious beliefs as well as task-specific knowledge. Task-specific knowledge auditors typically understand fraud indications and efficient detection techniques better. They are more likely to use thorough and detail-oriented audit techniques when paired with auditor religiosity, and they are also more open to signs of fraud they may come across while doing the audit. The researcher proposes a hypothesis:

H_{2c}: Effect of auditor religiosity has on detection of fraud is moderated by task specific knowledge

RESEARCH METHODS

This study used an association causal research design to investigate the impact of big data, computer-assisted audit techniques (CAATs), and auditor religiosity on fraud detection, with task-specific expertise serving as a moderating factor. To gather primary data for the current study, a survey instrument was distributed to a group of auditors working at the State Development Audit Agency's Representative Offices in Summe. The population of

Table 2. Descriptive Statistics

Variables	Theoritical		Actually		Standard Deviation
	Range	Median	Range	Mean	
BD	18 to 90	54	32 to 89	68.92	8.40
CAATs	17 to 85	51	38 to 85	70.32	9.26
AR	6 to 30	18	9 to 30	26.03	3.37
TSK	14 to 70	42	14 to 70	61.63	7.98
FD	11 to 55	33	22 to 55	48.75	6.16

Source: Processed of Primary Data, 2024

interest consists of 876 auditors, from which 276 were selected at a 5% significance level through a straightforward random sampling method based on Slovin's formula. Smart PLS 4 software is employed to transform the collected responses into numerical data and to assess them using the Structural Equation Model (SEM) with a Partial Least Squares (PLS) technique. The operational variables utilized in this study, along with their respective indicators, are presented in Table 1.

The research employs a structured questionnaire with closed-ended questions targeted at auditors from BPKP Representative Offices in Sumatra. A quantitative approach is applied to analyze the responses, presenting results in tabulated form to summarize questionnaire evaluations. Both the inner and outer models are evaluated using SEM; the inner model evaluates significance tests (t-test and MRA), R Square, effect size (F Square), and Q Square, while the outer model examines internal consistency reliability, convergent validity, and discriminant validity.

The selection of PLS-SEM as the analytical method is based on its ability to manage complex relationships between latent variables while accommodating non-normal data distributions and relatively small sample sizes. This method is particularly effective for exploratory investigations requiring theoretical validation and model refinement. To uphold ethical standards in data collection, respondent confidentiality and anonymity are strictly maintained. Participants provide informed consent and are briefed on the study's objectives, with the assurance that their participation is optional, and they are free to leave at any moment. The collected data are strictly used for academic purposes and stored securely to prevent unauthorized access.

RESULTS AND DISCUSSIONS

Gender, age, highest education level, functional auditor position (JFA), and term of work represent characteristics for respondents involved in this study. The survey included 100 women (45.45%) and 120 men (54.55%). Most respondents were aged between 21 and 40, with the largest share (34.09%) within the 31–40 age group. A bachelor's degree was held by the majority of respondents (68.18%), followed by diploma holders (20.91%) and master's degree holders (10.91%) regarding educational attainment. The most common functional auditor positions were First Auditor (29.09%) and Young Auditor (28.64%). Additionally, 68% of respondents had more than ten years of work experience.

The descriptive statistical analysis's findings (Table 2) show that respondents' average score for the Big Data construct is 68.92, much higher than the expected median of 54. This suggests that the majority of respondents have a positive opinion of big data. Similarly, the average score of 70.32 for the Computer Assisted Audit Techniques construct is higher than the predicted median of 51. This implies that, in contrast to the theoretical benchmark, respondents had a higher favorable opinion of certain auditing process strategies.

Additionally, the average score for the Auditor Religiosity construct is 26.03, which is far higher than the predicted median of 18. According to these results, respondents' levels of religiosity are typically higher than the theoretical reference point. Furthermore, the average score for the Task Specific Knowledge construct is 61.63, much higher than the anticipated median of 42. This indicates that the majority of respondents possess the knowledge to manage auditing duties efficiently.

Finally, the Fraud Detection construct shows an average score of 48.75, which is considerably above the estimated median of 33. This suggests that respondents have strong fraud detection awareness and are capable of

Table 3. Validity Result

Construct (Variable)	AVE	Decision
Big Data (BD)	0.807	Valid
CAATs	0.905	Valid
Auditor Religiosity (AR)	0.868	Valid
Task-Specific Knowledge (TSK)	0.787	Valid
Fraud Detection (FD)	0.897	Valid

Source: Processed Primary Data, 2024

Table 4. Reliability Result

Construct (Variable)	Composite Reliability (CR)	Cronbach's Alpha	Decision
Big Data (BD)	0.920	0.841	Reliabel
CAATs	0.956	0.956	Reliabel
Auditor Religiosity (AR)	0.928	0.843	Reliabel
Task-Specific Knowledge (TSK)	0.928	0.890	Reliabel
Fraud Detection (FD)	0.955	0.915	Reliabel

Source: Primary Data Processed, 2024

identifying fraudulent activities. The initial results of the outer model analysis include a comprehensive evaluation of the validity and reliability of constructs. Convergent validity of constructs (Table 3) was tested using Average Variance Extracted (AVE) with AVE ≥ 0.50 criteria. The test results show that all constructs meet the convergent validity criteria: Big Data (AVE = 0.807), CAATs (0.905), Auditor Religiosity (0.868), Task-Specific Knowledge (0.787), and Fraud Detection (0.897). Thus, the indicators used adequately explain the respective latent constructs, so it is appropriate to proceed to the analysis of the relationship between variables. Furthermore, in the Fornell & Larcker (1981) criteria test, it was revealed that each correlation between latent variables produced a value lower than the square root of the Average Variance Extracted (AVE) of the respective related constructs. Therefore, it can be concluded that each latent variable meets the criteria for discriminant validity.

The internal reliability of the constructs (Table 4) was tested using Cronbach's Alpha and Composite Reliability (CR) with a criterion of ≥ 0.70. The test results showed that all constructs reached this limit - Big Data (CR = 0.920; α = 0.841), CAATs (CR = 0.956; α = 0.956), Auditor Religiosity (CR = 0.928; α = 0.843), Task-Specific Knowledge (CR = 0.928; α = 0.890), and Fraud Detection (CR = 0.955; α = 0.915) - so the instrument was declared reliable. The reliability test results show that each construct has a Cronbach's Alpha and Composite Reliability value above the recommended threshold (≥ 0.70). This indicates the internal consistency of the measuring items so that the calculation of inter-construct relationships in subsequent analysis can be interpreted with higher confidence.

The coefficient of determination (R Square Adjusted) test was conducted using Smart PLS 4, resulting in the following data. From the Table 5, it can be seen that the Adjusted R Square value reaches 0.974. This result indicates that 97.4% of the variance in the Fraud Detection variable can be explained by the variance in the Big Data (X_1), Computer Assisted Audit Techniques (X_2), Task Specific Knowledge (X_3), and Auditor Religiosity (X_4) variables. Conversely, the remaining 2.6% is influenced by other factors outside the scope of this study. This interpretation implies that the higher the contribution of these three exogenous variables to the endogenous variable, the stronger the relationship in the structural equation. Referring to the rule of thumb criteria adopted from Bollen, (1989) & Hair et al., (2013), it can be concluded that this model is categorized as a strong model, with a value of 0.974 exceeding the threshold of 0.67 and 0.75, as recommended by these criteria.

Hair et al., (2022: 209) explained that the effect size F^2 facilitates the assessment of the contribution of an exogenous construct to the R^2 value of the predictor latent variable. Values of F^2 at 0.02, 0.15, and 0.35 indicate small, medium, or large effects, respectively, of a predictor construct on an endogenous construct. The F^2 test was conducted using Smart PLS 4 with the following results, as presented in Table 6.

Based on Table 6, it is observed that the effect size F^2 values for Big Data and Computer Assisted Audit Techniques are 0.001 (< 0.02), indicating that X_1 and X_2 do not have significant effect sizes. However, the effect size F^2 value for Religiosity of Auditors is 15.028 (> 0.35), indicating that it has a large effect size. Meanwhile, the effect size F^2 value for the Task Specific Knowledge variable is 0.024 (> 0.02), suggesting that X_4 has a small effect size. Additionally, the effect size F^2 values for the moderation effects on BD_TSK, CAATs_TSK, and RA_TSK are 0.001 (< 0.005), indicating that M_1, M_2, and M_3 do not have significant effect sizes.

Based on Table 7, it can be seen that the value of Q^2 prediction reaches 0.973. This result indicates that the model has strong predictive relevance. A Q^2 prediction value approaching 1 indicates that the model has high pre-

Table 5. R Square

	R Square	R Square Adjusted
Fraud Detection	0.974	0.974

Source: Primary Data Processed, 2024

Table 7. Q^2 Predictive Relevance

	RMSE	MAE	Q^2_predict
Fraud Detection	0.168	0.096	0.973

Source: Primary Data Processed, 2024

Table 6. Effect Size F^2

	Fraud Detection
Big Data	0.001
Computer-Assisted Audit Techniques	0.000
Auditor Religiosity	15.028
Task Specific Knowledge	0.024
BD_TSK	0.001
CAATs_TSK	0.001
RA_TSK	0.001

Source: Primary Data Processed, 2024

Table 8. Test of Significance

Construct	OS	T Statistics	P-Values	Result
BD -> PF	-0.006	0.400	0.345	$H_{a1.a}$ Refused
CAATs -> PF	-0.001	0.041	0.484	$H_{a1.b}$ Refused
RA -> PF	0.959	65.127	0.000	$H_{a1.c}$ Accepted
TSK -> PF	0.044	2.195	0.014	-
BD_TSK -> PF	-0.008	0.521	0.301	$H_{a2.a}$ Refused
CAATs_TSK -> PF	0.008	0.411	0.341	$H_{a2.b}$ Refused
RA_TSK -> PF	0.003	0.249	0.402	$H_{a2.c}$ Refused

Source: Processed of Primary Data, 2024

dictive ability. According to the first A sample value is hereby presented for consideration -0.006 (-0.6%) (Table 8), it is found that Big Data harms Fraud Detection, which, as indicated by the t-statistics value of 0.400 < the t-table value of 1.6518, is not statistically significant. Furthermore, insignificance (> 0.05) is shown by the derived p-value of 0.345. Thus, it can be inferred from the study hypothesis that $H_{01.a}$ is accepted and $H_{a1.a}$ is denied, suggesting that fraud detection is not much impacted by big data.

In line with the first, the t-statistic value of 0.041 < the t-table value of 1.6518 indicates that Computer Assisted Audit Techniques (CAATs) impair Fraud Detection, which is not statistically significant. A sample value of -0.001 (-0.1%) is thus offered for consideration. Furthermore, insignificance (> 0.05) is shown by the derived p-value of 0.484. Consequently, it may be inferred from the study hypothesis that $H_{01.b}$ is accepted and $H_{a1.b}$ is rejected, suggesting that computer-assisted audit techniques have no discernible effect on fraud detection.

In line with the first A sample value of 0.959 (95.9%) is provided for consideration. The t-statistic value of 65.127 > the t-table value of 1.6518 indicates that the religiosity of auditors has a positive and substantial impact on fraud detection. Furthermore, significance (< 0.05) is shown by the computed p-value of 0.000. Thus, it may be inferred from the research hypothesis that $H_{01.c}$ is rejected and $H_{a1.c}$ is accepted, suggesting that auditor religiosity significantly affects fraud detection.

In line with the first, for example, the value for your consideration. -0.008 (-0.8%), the t-statistic value of 0.521 < the t-table value of 1.6518 indicates that the Task Specific Knowledge has a positive impact on the effect of Big Data on Fraud Detection, which is not statistically significant. Furthermore, insignificance (> 0.05) is shown by the derived p-value of 0.301. Thus, according to the research hypothesis, it can be said that task-specific knowledge does not mitigate the impact of big data on fraud detection, since $H_{02.a}$ is accepted and $H_{a2.a}$ is rejected.

In line with the first Task Specific Knowledge has a favorable impact on the effect of Computer Assisted Audit Techniques on Fraud Detection, according to a sample value of 0.008 (0.8%) that is provided for consideration. However, the t-statistic value of 0.411 < the t-table value of 1.6518 indicates that this impact is not statistically significant. Furthermore, insignificance (> 0.05) is shown by the derived p-value of 0.341. The impact of computer-assisted audit techniques on fraud detection is not moderated by task-specific knowledge, as demonstrated by the rejection of $H_{a2.b}$ and acceptance of $H_{02.b}$ based on the research hypothesis.

In line with the first, the influence of auditors' religiosity on fraud detection is positively impacted by task-specific knowledge, according to a sample value of 0.003 (0.3%) that is provided for consideration. However, the t-statistic value of 0.249 < the t-table value of 1.6518 indicates that this impact is not statistically significant. Furthermore, insignificance (> 0.05) is shown by the derived p-value of 0.402. Thus, according to the research hypothesis, it can be said that Task Specific Knowledge does not mitigate the effect of auditors' religiosity on fraud detection, with $H_{02.c}$ being accepted and $H_{a2.c}$ being denied.

The Influence of Big Data on Fraud Detection

The findings of the data study show that fraud detection is not much impacted by big data. There are several reasons for this. First off, even though Big Data has enormous potential to improve fraud detection through in-depth data analysis, auditors find it extremely difficult to comprehend the volume and complexity of data. Secondly, the variety of data formats available in Big Data adds layers of complexity that require specialized technical skills to process effectively. Thirdly, the high velocity of data also makes it difficult for auditors to process and analyze data within limited timeframes. Lastly, although auditors have a positive perception of the accuracy (veracity) of data, they also recognize that the costs involved in obtaining and managing Big Data are very high, which may be a significant barrier to its implementation. The Unified Theory of Technology Acceptance and Use (UTAUT), developed by Venkatesh et al. (2003) demonstrates that while auditors believe Big Data is useful for assisting in the discovery of fraud factors, such as the effort required to manage large and complex data, as well as the high cost of obtaining and utilizing Big Data, may reduce their motivation to adopt the technology. Thus, UTAUT elucidates that the acceptance and use of Big Data by auditors are not only influenced by perceptions of its benefits in fraud detection but also by elements such as related fees, social support, and convenience of usage. Therefore, if auditors encounter such obstacles while implementing Big Data, even though it has the potential to improve fraud detection, its impact could not be substantial. This finding is consistent with previous research by Sembiring & Widuri (2023), although earlier investigation by Syahputra & Afnan (2020), Handoko et al. (2022), Bandiyono (2023), and Surono (2023) state otherwise.

The Influence of CAATs on Fraud Detection

CAATs have no discernible effect on the detection of fraud, according to the data study. This is because, even though auditors view Excel as a useful tool for auditing, its features and sophistication might not be enough to identify more intricate fraud. The framework for elucidating the connection between fraud detection and the deployment of CAATs is the Unified Theory of Acceptance and Use of Technology (UTAUT). Performance expectancy, effort expectancy, social impact, and enabling conditions are the four primary components that UTAUT takes into account. In this situation, Excel is still insufficient for identifying more complex fraud, even though auditors have favorable attitudes, feel encouraged by colleagues, and have access to the required resources. The inability of Excel to analyze extremely complicated data or identify subtler fraud patterns—tasks that frequently call for more specialized and sophisticated audit tools—is the cause of this. Furthermore, UTAUT clarifies that even when auditors believe Excel is beneficial and easy to use, and there is social support and suitable settings, these elements do not always result in improved efficacy in detecting fraud. This suggests that the quality and appropriateness of the audit tool for particular activities, including fraud detection, are also very important, in addition to technology adoption. These results align with the study carried out by Choirunnisa & Rufaedah (2022) and Kamal (2022). Nevertheless, research by Olasanmi (2013), Atmaja (2016), Fauzi et al. (2020), and Samagaio & Diogo (2022), they provide diverse findings and demonstrate that CAATs have no discernible effect on fraud detection. The research conducted by Widuri & Gautama (2020), disagrees with this by employing a qualitative method, suggesting that the use of CAATs is essential to fraud detection.

The Influence of Auditor Religiosity on Fraud Detection

The data analysis reveals that auditor religiosity has a significant influence on fraud detection. The notion of attribution, put out by Heider (1958), serves as the foundation for elucidating the research findings. This theory examines how people use situational attributions—which are connected to the context—or dispositional attributions—which are related to the individual—to explain events and behavior. In this regard, more religious auditors are more likely to view unethical action as bad and to have more favorable dispositional attributions toward ethical behavior, which increases the possibility that they will catch fraud. According to attribution theory, auditors' religion influences the situational and dispositional attributions they make to explain events and behaviors linked to accounting fraud. More accurate situational attributions and more positive dispositional attributions can be enhanced by higher auditor religiosity, which will help auditors identify accounting fraud. Because they are more likely to think that moral behavior should always be upheld, whether or not the circumstances are favorable, religious auditors may be more alert to signs of deception. Therefore, auditors' judgment and response to potentially fraudulent circumstances are influenced by their level of religiosity in addition to their intrinsic drive. These results align with the study carried out by Fadilah et al. (2020) and Bandiyono (2023). This illustrates how religion affects auditors' ability to spot fraud. This study supports the research by Suci et al. (2022). This demonstrated how auditors' capacity to identify fraud is greatly impacted by their level of religiosity.

The Moderating Role of Task-Specific Knowledge on the Relationship Between Big Data and Fraud Detection

The findings of the investigation demonstrate that the impact of big data on fraud detection is not moderated by task-specific knowledge. There are several causes behind this. First off, even though Big Data offers a wide range of resources for data analysis, auditors' technical proficiency and knowledge of data analysis tools and methodologies are crucial to their ability to use Big Data successfully. Task-specific knowledge, which is more related to a deep understanding of specific audit procedures and practices, may not be sufficient to optimize the use of big data to identify fraud without the use of specialized data analysis abilities. Second, the auditor's specific job expertise might not be sufficient to handle the complexity and volume of Big Data, which calls for more advanced and specialized analytical techniques. The Unified Theory of Technology Acceptance and Use (UTAUT), developed by Venkatesh et al., (2003) may clarify how these factors relate to one another and how using Big Data requires proper infrastructure and technological assistance. Even if auditors possess task-specific knowledge, they may not be able to use Big Data efficiently if firms do not offer the required training or resources. The effectiveness of using Big Data in fraud detection greatly depends on how competent and at ease auditors feel using the technology, even when they have specialized expertise about audit responsibilities. How much Big Data may influence fraud detection depends on several factors, including performance expectations and efforts, societal impact, and enabling conditions. Even if auditors have sufficient task-specific knowledge about audit activities, their discomfort or lack of expertise with Big Data may limit the technology's value.

The Moderating Role of Task-Specific Knowledge on the Relationship Between CAATs and Fraud Detection

The findings of this study indicate that task-specific knowledge does not moderate the relationship between

Computer-Assisted Audit Techniques (CAATs) and fraud detection. There are several reasons behind this. First off, by offering advanced and automated data analysis, CAATs are instruments created to improve the efficacy and efficiency of the audit process. However, task-specific knowledge may not adequately address the particular abilities needed to master the technical usage of CAATs. Secondly, effective use of CAATs also requires a deep understanding of information technology and data analysis, which goes beyond the scope of task-specific knowledge. Therefore, although auditors have a profound knowledge of audit tasks, this alone is insufficient to optimize the use of CAATs without additional technical skills. The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) and the cognitive dissonance theory by Festinger (1957) help explain why Task Specific Knowledge does not moderate the Impact of CAATs on fraud detection. While CAATs have the potential to enhance audit effectiveness, the ability to leverage this technology to its fullest extent heavily depends on the technical skills and comfort level of auditors in using the technology, which may not be fully supported by specific audit task knowledge.

The Moderating Role of Task-Specific Knowledge on the Relationship Between Auditor Religiosity and Fraud Detection

The findings of the data analysis show that the influence of auditor religiosity on fraud detection is not mitigated by task-specific knowledge. This is because the ways that religion and task-specific knowledge affect fraud detection are distinct. The honesty and dedication to fraud detection of auditors can be strongly impacted by their religion, which includes strong moral and ethical convictions. Meanwhile, task-specific knowledge is more focused on technical and procedural aspects of auditing. The combination of the two does not necessarily result in stronger synergy in fraud detection, as ethical motivation and technical skills may work independently. The attribution theory by Heider (1958) and cognitive dissonance theory by Festinger (1957) can explain why Task-specific knowledge does not decrease auditor religiosity's influence on fraud detection. According to the attribution hypothesis, religious auditors are more motivated internally to identify fraud because of their moral principles. According to the cognitive dissonance theory, people feel psychologically uncomfortable if they believe they don't know enough. Task-specific knowledge doesn't moderate the Impact of religiosity because these two factors operate on different levels: religiosity motivates morally and ethically, while task-specific knowledge pertains to technical and procedural skills. Thus, although religious auditors are motivated to detect fraud, their ability to do so is not strengthened or weakened by their task-specific knowledge. Religiosity serves as a strong internal motivator that is not directly impacted by the technical knowledge they possess. The association between religion and fraud detection cannot be moderated by cognitive dissonance alone, even when it causes discomfort if people feel they lack technical competence.

CONCLUSIONS

Fraud detection is not much impacted by big data, and identification of fraudulent activity is not significantly impacted by the use of computer-assisted auditing procedures. Nonetheless, expertise in particular jobs is essential for identifying fraud. However, task-specific knowledge does not lessen or alter the impact of computer-assisted auditing approaches in detecting fraud, nor does it alter or diminish the effect of Big Data on fraud detection. Furthermore, task-specific information has no bearing on the function of auditor religiosity in fraud detection since it neither lessens nor changes its influence during the audit process.

The questionnaire has been distributed both online and by paper forms, although direct distribution was not possible due to access issues outside of South Sumatra Province. Three exogenous variables and a moderating variable were also included in the research model, which explained 92.6% of the variation in fraud detection. This suggests, therefore, that fraud detection may also be impacted by other unobserved factors that are not taken into account by the model.

Additionally, the questionnaire distribution was postponed until October 2023 and continued until January 2024 due to the lengthy study permission application process. This time limit, together with the auditors' geographical locations and work obligations, could have impacted the sample's representativeness and the findings' applicability to actual situations.

To provide a more thorough study that includes comparisons between provinces and islands, further research is recommended to expand the sample size of State Development Audit Agency auditors throughout Indonesia. It is also advised to broaden the range of variables, especially by looking at additional possible elements that can affect fraud detection, such as auditor workload, personality types, whistleblower protections, and whistleblowing mechanisms. Furthermore, it would be advantageous to think about increasing the significance level in subsequent research to a range of 0.1% to 1%, as this modification may improve the findings' generalizability and lower the possibility of statistical errors, particularly when dealing with smaller sample sizes in particular areas.

REFERENCES

Afriana. (2019). Pengaruh Pengalaman Kerja, Religiusitas and Skeptisme Profesional Terhadap Kemampuan Auditor Internal dalam Mendeteksi Kecurangan. *Jurnal Akademik Pendidikan Ekonomi, 6*(1).

Atmaja, D. (2016). Pengaruh Kompetensi, Profesionalisme, and Pengalaman Audit Terhadap Kemampuan Auditor Baand

Pemeriksa Keuangan (BPK) dalam Mendeteksi Fraud dengan Teknik Audit Berbantuan Komputer (TABK) Sebagai Variabel Moderasi. *Media Riset Akuntansi, Auditing & Informasi, 16*(1), 53-68.

Bandiyono, A. (2023). Fraud Detection: Religion In The Workplace Big Data Analytics. *Jurnal Akuntansi, 27*(2), 380-400.

Betri. (2022). *Akuntansi Forensik and Audit Investigatif (1st ed.)*. Pelembang: NoerFikri Offset.

Bonner, S. E. (1990). Experience Effect in Auditing : The Role of Task-Specific Knowledge. *The Accounting Review, 65*(1), 72–92.

Braun, R. L. & Davis, H. E. (2003). Computer-assisted audit tools and techniques: analysis and perspectives. *Managerial Auditing Journal, 18*(9), 725–731.

Chen, C. L. P. & Zhang, C.-Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Information Sciences, 275*, 314–347.

Choirunnisa, R. & Rufaedah, Y. (2022). Pengaruh Kompetensi Auditor and Pemanfaatan Teknologi Informasi Terhadap Pendeteksian Fraud. *Jurnal Akuntansi Trisakti, 9*(1), 119-128.

Fadilah, N., Patra, I. K. & Rahmawati. (2020). *Pengaruh Religiusitas and Rasionalisasi Terhadap Pendeteksian Kecurangan pada PT. PLN (Persero) ULP Kota Palopo* (Doctoral dissertation, Universitas Muhammadiyah Palopo).

Fauzi, M. R., Anwar, C. & Ulupui, I. G. K. A. (2020). Pengaruh Independensi, Pengalaman, and Penerapan Teknik Audit Berbantuan Komputer (TABK) terhadap Efektivitas Pelaksanaan Audit Investigatif dalam Mendeteksi Kecurangan. *Jurnal Akuntansi, Perpajakan dan Auditing, 1(1)*, 1–15.

Festinger, L. (1957). A theory of cognitive dissonance. *Row, Peterson, New York.*

Fiske, S. T. & Taylor, S. E. (1991). *Social Cognition* (2nd ed.). Mcgraw-Hill.

Ghufron, M. N. & Risnawati. (2012). *Teori-teori Psikologi. Ar-Ruzz Media.*

Glock, C. Y. & Stark, R. (1965). *Religion and Society in Social Tension*. Rand McNally and Company.

Govinand, K., Cheng, T. C. E., Mishra, N. & Shukla, N. (2018). Big data analytics and application for logistics and supply chain management. *Transportation Research Part E: Logistics and Transportation Review, 114,* 343–349.

Handoko, B. L., Rosita, A., Ayuanda, N. & Budiarto, A. Y. (2022). The impact of big data analytics and forensic audit in fraud detection. In *2022 12th International Workshop on Computer Science and Engineering, WCSE (pp. 67-71).*

Heider, F. (1958). *The psychology of interpersonal relations*. John Wiley & Sons Inc. https://doi.org/10.1037/10628-000

Hipgrave, S. (2013). Smarter fraud investigations with big data analytics. *Network Security*, 2013(12).

Johnson, P. E., Grazioli, S., & Jamal, K. (1993). Fraud detection: Intentionality and deception in cognition. *Accounting, Organizations and Society, 18*(5), 467–488.

Kamal, A. (2022). Teknologi Informasi and Skeptisme Profesional terhadap Fraud Detection Skills Auditor Internal Pemerintah. *YUME : Journal of Management*, 295–313.

Karyono. (2013). *Forensic fraud*. Yogyakarta: CV Andi.

KBBI Daring. (2016). *Deteksi*. Badan Pengembangan dan Pembinaan Bahasa, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia. https://kbbi.kemdikbud.go.id/entri/deteksi

Kumaat, V. G. (2011). *Audit internal*. Jakarta: Erlangga.

Kusumawaty, M., & Betri, B. (2019). Pengaruh pengalaman audit, beban kerja, task specific knowledge, tipe kepribadian terhadap pendeteksian kecurangan laporan keuangan (Studi kasus kantor akuntan publik Kota Palembang). *Balance: Jurnal Akuntansi dan Bisnis, 4*(1), 537-548.

Lembayung, H. D. & Chomsatu, Y. (2021). Determinan Pendeteksian Fraud Pada KAP di Surakarta. *Jurnal Manajemen, Ekonomi, Keuangan and Akuntansi* (MEKA), 253–260.

Lestari, D. & Indrawati, E. S. (2017). Hubungan antara Religiusitas dengan Penyesuaian Diri pada Siswa and Siswi Kelas VII Yayasan Pondok Pesantren Futuhiyyah Mranggen Kabupaten Demak. *Jurnal Empati*, 6(14), 307–312.

Libby, R. (1995). *The role of knowledge and memory in audit judgment.* Cambridge University Press.

Lin, C. W., & Wang, C. H. (2011). A selection model for auditing software. *Industrial Management & Data Systems*, 111(5), 776-790.

Moyes, G. D. & Hasan, I. (1996). An empirical analysis of fraud detection likelihood. *Managerial Auditing Journal*, 11(3).

Muzdalifah & Syamsu, N. (2020). Red Flags, Task Specific Knowledge and Kemampuan Auditor dalam Mendeteksi Kecurangan. *Jurnal Ekonomi Pembangunan*, 6(2), 92–101.

Olasanmi, O. O. (2013). Computer aided audit techniques and fraud detection. *Research Journal of finance and accounting*, 4(5), 67-80.

Perdana, A. (2020). *Data analytics: keterampilan teknis akuntan dan auditor di era digital*. Madza Media.

Sagiroglu, S., & Sinanc, D. (2013, May). Big data: A review. In *2013 international conference on collaboration technologies and systems (CTS)* (pp. 42-47). IEEE.

Samagaio, A., & Diogo, T. A. (2022). Effect of computer assisted audit tools on corporate sustainability. *Sustainability*, 14(2), 705.

Sari. (2019). The Effect of Task Specific Knowledge in Fraud Detection Skill: Internal Audit Effectiveness as A Intervening Variable On BPK Representative of Riau and Kepri Province. *Jurnal Riset And Pengembangan Ekonomi Islam*, 3(2).

Sari, Y., Fajri S, Rd. A. & Syuriansyah, T. (2012). Religiusitas pada Hijabers Community Bandung. *Prosiding SNaPP2012: Sosial, Ekonomi, And Humaniora*, 3, 311–318.

Sembiring, F. N. B. & Widuri, R. (2023). The Effect of Auditor Experience, Big Data and Forensic Audit as Mediating Variables on Fraud Detection. Journal of Theoretical and Applied Information Technology, 101(6).

Suci, C. F., Putra, R. S. & Syaf, R. (2022). The Effect of Red Flags, Auditor's Competence, Religiusity and Professional Skepticism on The Ability of Internal Auditors in Detecting Fraud. *Digital Business Journal*, 1(1).

Surono. (2023). Dampak Pemanfaatan Big Data and Audit Forensik dalam Pendeteksian Fraud. *Jurnal Ilmiah Multidisiplin*, 1(9), 103–111.

Syahputra, B. E. & Afnan, A. (2020). Pendeteksian Fraud: Peran Big Data and Audit Forensik. *Jurnal Aset (Akuntansi Riset)*, 12(2), 301–316.

Tirta, R. & Sholihin, M. (2004). The Effects of Experience and Task-Specific Knowledge on Auditors' Performance in Assesing

a Fraud Case. *Jurnal Akuntansi And Auditing Indonesia*, 8(1).
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 27(3), 425-478. https://doi.org/10.2307/30036540
Widuri, R. & Gautama, Y. (2020). Computer-Assisted Audit Techniques (CAATs) for Financial Fraud Detection: A Qualitative Approach.
Yusrianti, H. (2015). Pengaruh Pengalaman Audit, Beban Kerja, Task Specifi Knowledge Terhadap Pendeteksian Kecurangan Laporan Keuangan (Studi pada KAP di Sumater Bagian Selatan). Jurnal Manajemen And Bisnis Sriwijaya, 13.
Zamzami, F., Duta Nusa, N. & Arifin, F. I. (2021). *Sistem Informasi Akuntansi*. UGM Press.

Appendix I- Questionnaire

Variable	Dimension	Indicator
Fraud detection (Y)	1. Ability to detect fraud	a. Develop fraud detection measures profilling fraud action
		b. Document and information testing
		c. Identification of causes of fraud
	2. Have a high vigilance attitude	a. Understand fraud
		b. Be careful in fraud decisions
		c. Find and secure relevant documents
	3. Have accuracy	a. Find reliable evidence
		b. Collect, examine, assess evidence
	4. Have accuracy	a. Understand the internal control system
		b. Effectiveness of methods and procedures
Big Data (X_1)	1. Volume (large size dimension)	a. Hadoop Database
		b. Fast growing
		c. Difficult to manage
	2. Variety (variety of data types)	a. Wealth of information
		b. Variety of sources
		c. Structured
		d. Unstructured
	3. Velocity (speed of data creation)	a. Quick acquisition
		b. Real-time data
		c. High frequency update
	4. Veracity (uncertainty regarding accuracy and reliability)	a. Very precise
		b. Very accurate
		c. Not trustworthy
		d. Reliable
	5. Value (has a high value when processed with the right method)	a. Helpful
		b. High cost of aquisition
		c. High cost to acess
		d. Benefits are proportional to costs
Computer Assisted Audit Techniques (X_2)	1. The need to use CAATs (Perceived Usefulness)	a. Assist with fraud checks
		b. Previously, general fraud
		c. Better role in fraud detection
		d. Effective audit time
		e. Audit cost efficiency
		f. More credible
	2. easeness CAATs (Perceived Ease of Use)	a. Audit data is neatly indexed
		b. Audit data is securely stored
		c. Easy to use
		d. Easy to understand
		e. Easy to become skillful
		f. Can operate CAATs

Variable	Dimension	Indicator
		g. Routine CAATs in the agency
	3. Attitude Toward Using	a. Stay on top of work
		b. Important role with CAATs
	4. Acceptance of CAATs	a. Improve employee performance
		b. Increase productivity
Religiosity Auditor (X_3)	1. High level of implementation of religious values in daily life	a. Behavioral reference basis
		b. Religious values are important from an early age
	2. Active involvement in religious activities	a. Engaged and punctual in worship
		b. Active in religious organizations
	3. Level of trust in religious leaders	a. Respect religious leaders
		b. Discussion with religious leaders
Task Specific Knowledge (Z)	1. Knowledge	a. Accounting and auditing knowledge
		b. Legal and regulatory knowledge
		c. Differentiation of opinion and fact
		d. Adaptability in complex situations
		e. Checks that should be there
		f. Unstructured approach
		g. Financial statement irregularity analysis
	2. Auditor capacity in their assessment of fraud	a. Knowledge of fraud drivers
		b. Knowledge of criminology and victimology
		c. Auditor communication in fraud detection
		d. Fraud detection experience
		e. Development of fraud knowledge
		f. Focus on fraud risk factors
		g. Identification of high risks and additional procedures

Source: Processed of Primary Data, 2024