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THE EFFECT OF RED FLAGS, TASK SPECIFIC KNOWLEDGE, BRAINSTORMING, AND DATA ANALYTICS ON AUDITORS' ABILITY TO DETECT FRAUD

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ABSTRACT

The purpose of this study is to determine the effect of red flags, task-specific knowledge, brainstorming, and data analytics on auditors' ability to detect fraud (a study of the Riau Provincial Inspectorate). The quantitative research is an method that implemented in this study. The Riau Provincial Inspectorate office employs sixty-three auditors that make up the research population. Sixty-three respondents made up the study's sample, which was drawn from the total population via saturated sampling, also known as census sampling. A Likert scale was employed as the measuring tool in this study, and the basic data came straight from statements (questionnaires) given to respondents. The IBM Statistical Product and Service Solutions (SPSS) version 29 computer program was utilized to do multiple linear regression analysis, which was the method of data analysis used in this study. Based on the results of the determination test, the R Square value was 0.901 or 90.1%, meaning that fraud detection was influenced by the variables of red flags, task specific knowledge, brainstorming, and data analytics. Other factors that were not investigated in this study had an impact on the remaining 9.9%. The study's findings suggest that auditors' capacity to identify fraud is significantly impacted by red flags, task specific knowledge, and data analytics. In the meantime, auditors' capacity to identify fraud is not significantly impacted by brainstorming.

INTRODUCTION

High economic pressures often trigger individuals to engage in unethical acts for personal gain. Unintentional mistakes are referred to as errors, while intentional mistakes constitute fraud, which is classified as a criminal offense (Ramadhani et al., 2024). The phenomenon of white-collar crime has become a major challenge in achieving good governance in both the public and private sectors. Based on Auditing Standard No. 99 (SAS No. 99), fraud is defined as a deliberate or intentional act to produce falsification or misrepresentation of material information in audited financial statements. Fraud consists of three main categories, namely asset misappropriation, fraudulent misstatement and corruption (Ngesti & Djamil, 2024). Fraudulent practices such as financial statement manipulation, document destruction, and profit mark-ups pose serious challenges for auditors in maintaining the reliability of financial statements. The most common cases are manipulation of financial statement records, destruction of documentary evidence, and inappropriate profit markups, resulting in losses for other parties. The internal auditor, as the person conducting the examination, has several roles: fraud prevention, fraud detection, and fraud investigation.

According to data from the Association of Certified Fraud Examiners (ACFE) in 2022, 80% of perpetrators commit crimes due to a lack of internal controls and poor management oversight within companies, making auditors heavily responsible for detecting and uncovering accounting fraud that could harm certain parties (Juliyanti & Muslim, 2022). Auditors continue to strive to maximise various techniques and methods in improving internal control in accordance with applicable auditing standards (Ramadhani et al., 2024) in order to maintain the credibility and integrity of financial statements and continue to maximise the effectiveness of recovering state assets.

Data from the Association of Certified Fraud Examiners (ACFE) in 2022 shows that 80% of fraud cases occur due to weak internal controls and suboptimal management, so auditors have a big responsibility in detecting and uncovering accounting fraud that harms many parties (Juliyanti & Muslim, 2022). To address this challenge, auditors need to have a deep understanding of the company's business activities, recognize potential fraud, and have the skills to spot signs of irregularities in financial statements. In carrying out their duties, auditors are expected to uphold the principles of integrity, objectivity, and professionalism, which form the basis of auditing in accordance with the guidelines of the Indonesian Public Accountants Association (LAPI).

The ability of auditors to detect fraud is greatly influenced by internal and external factors. Internal factors include red flags and task-specific knowledge, which is the ability of auditors to recognize signs of fraud and deeply understand the tasks and audit processes being carried out (Ramadhani et al., 2024). External factors such as brainstorming and the use of data analytics also play an important role. Brainstorming allows auditors to discuss and exchange ideas critically, while data analytics supports auditors in analyzing big data to find anomalous patterns that indicate fraud (Anisa & Novita, 2023).

In the context of regional government, the Provincial Inspectorate, as the Internal Government Supervisory Agency (APIP), plays a central role in ensuring clean and accountable governance (Djamil, 2023). Based on Government Regulation No. 60 of 2008, the Provincial Inspectorate functions to conduct audits, reviews, evaluations, and other supervisory activities in the implementation of government tasks (Kemenkeu.go.id, 2008). However, a number of reports show that the effectiveness of internal control in Indonesia still needs to be improved. In a 2024 study by the

Association of Certified Fraud Examiners (ACFE), there were approximately 1,921 cases of fraud throughout the year affecting organizations or companies in 138 countries, causing total losses of more than $3.1 billion. The following is the median loss for international fraud cases in 2024:

Source: ACFE, 2024

Transparency International Indonesia (TII) noted in 2023 that Indonesia's Corruption Perception Index (CPI) ranking fell from 110 to 115, with a score declining from 38 to 34, indicating a worsening perception of public integrity (ICW, 2023). There were 888 corruption suspects in Indonesia throughout 2024, with Riau Province topping the list with the highest number of suspects, with 76. ICW believes the high number of suspects at the regional level reflects a weak oversight system and low integrity and accountability in regional governance (Source: riauaktual.com, 2025). Riau Province is one of the regions with the highest number of corruption cases in Indonesia, with 76 suspects in corruption cases in 2024 (riauaktual.com, 2025). Government procurement of goods and services, as regulated in Presidential Regulation Number 16 of 2018, plays a strategic role in supporting national development and the quality of public services. Therefore, the effectiveness of the Provincial Inspectorate's internal oversight function is a key indicator of good or bad governance through the strengthening of risk management, control, and organisational governance. However, the findings of the Audit Board of the Republic of Indonesia (BPK RI) Representative Office of Riau Province in 2022 indicate that this control is still weak, as reflected in the failure of the project to build six electric umbrellas at the An-Nur Grand Mosque in Pekanbaru, valued at Rp43 billion, due to overpayment, non-compliance with contract specifications without the approval of the Implementing Officer (PPK), and work that was not realised as acknowledged (riau.bpk.go.id, 2024). A similar phenomenon was also found in the Islamic Centre Pekanbaru Landscape Development Project for the 2022 Fiscal Year, where there was a shortage in the volume of work worth billions of rupiah despite the contract addendum, indicating a weak role for the Project Implementing Officer (PPK), the Technical Project Implementing Officer (PPTK), and the supervisory consultant, and resulting in financial losses for the local government (buserkriminalitas.com, 2024).

Auditors working in the Riau Provincial Inspectorate are expected to implement a professional and technology based approach in detecting indications of fraud. The ability of auditors to detect fraud is believed to be influenced by four important factors, namely red flags, task-specific knowledge, brainstorming, and data analytics. Red flags serve as early warning signs of fraud (Ramadhani et al., 2024) while task specific knowledge enables auditors to gain a deeper understanding of the internal conditions of the audited organization (Masnur et al., 2023). Brainstorming encourages collaboration among auditors in identifying potential fraud through open discussion and experience sharing (Laksana & Achmad, 2020) while the application of data analytics provides greater efficiency and accuracy in analyzing complex data patterns (Prasetyo et al., 2024).

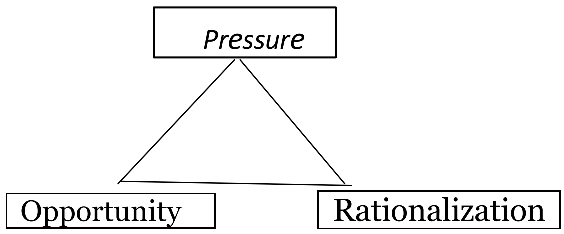
As data complexity and information volume in the public sector increase, the Riau Provincial Inspectorate has begun adopting Big Data Analytics (BiDiCs) technology to support digital oversight. This technology helps auditors trace cash flows, conduct asset tracing, and identify potential fraud based on more integrated data (Anisa & Novita, 2023). However, the effectiveness of this technology depends on the competence of auditors in operating and analyzing data appropriately. Previous research conducted by Ramadhani et al. (2024) revealed that auditors' ability to detect fraud is significantly impacted by red flags, task-specific knowledge, and brainstorming. On the other hand, Prasetyo et al. (2024) emphasized the important role of data analytics in supporting the detection of internal fraud.

Based on a number of phenomena, previous research results, and the continuing weaknesses in supervisory practices at the Riau Provincial Inspectorate, this study aims to analyze the influence of red flags, task-specific knowledge, brainstorming, and data analytics on auditors' ability to detect fraud. This study is expected to provide empirical understanding of the factors that can improve the effectiveness of government auditors in detecting fraud, as well as contribute to the development of technology-based oversight systems in the public sector.

LITERATURE REVIEW

Fraud Triangle Theory

The Fraud Triangle Theory (Cressey, 1953) in (Tuanakotta, 2016) explains that fraud can be caused by a number of factors, namely pressure, opportunity, and rationalization (Anisa & Novita, 2023). Based on these factors, the fraud triangle theory is used in this study as a basis, with a focus on variables that represent pressure, opportunity, and rationalization. The fraud triangle theory factor scheme:



Attribution Theory

Fritz Heider first proposed Attribution Theory in 1958. This theory explains methods for identifying the reasons and influences behind people's actions and their responses to life events. By analyzing whether human behavior is influenced by internal forces, namely dispositional attributions (individual dispositions or characteristics), and external forces, namely situational attributions (organizational cultural factors), it can influence the way individuals behave and act (Utama & Rohman, 2023).

Fraud

In this era of globalization and business complexity, managing fraud risk poses a major challenge for organizations. The Institute of Internal Auditors (IIA), an international auditing organization in the United States, explains that taking advantage of others, causing financial and non-financial losses, damaging a company's reputation, and potentially jeopardizing a company's ability to continue operating are all considered forms of fraud. Fraud can take various forms, such as forgery, embezzlement, internal conspiracy, and deception (Gaswira, 2024).

Auditor's Ability To Detect Fraud

Robbins (2017) defines ability as "an individual's current capacity to perform the various tasks in a job," which is defined as an individual's capacity to carry out a specific task (Atmaja, 2016). An individual's overall ability basically consists of two groups of factors, namely intellectual ability, which includes the ability to carry out mental activities such as thinking, reasoning, and solving problems and physical ability, which includes the ability to carry out tasks that require comparable strength, skills, and traits.

Red Flags

Red flags are warning signs for auditors indicating irregularities or fraud that may occur (Ramadhani et al., 2024). An attitude of curiosity and critical assessment of audit evidence (skepticism) can be enhanced by red flags. And they are effective in about 20% of cases for auditors in detecting fraud in financial statement audits (Gizta, 2020). Fraud can be detected by auditors with high competence when auditors encounter red flags at a high level (Achmad & Galib, 2022).

In line with research conducted by Fitriawati (2024), Masri et al. (2021), and Ramadhani et al. (2024), the findings indicate that red flags have a positive and significant impact on fraud detection. This research suggests that an auditor with good knowledge of red flags will be more sensitive in detecting fraud compared to an auditor with less knowledge of red flags. This differs from the findings of research conducted by Desi Susilawati et al. (2022), which found that red flags have a negative and non-significant impact on an auditor's ability to detect fraud. This is due to the fact that the red flags that appeared were not sufficient to indicate fraud.

Based on the above description, the following hypothesis can be formulated: **H1**: Red flags have a significant positive effect on auditors' ability to detect fraud.

Task Specific Knowledge

The context can be identified and the internal circumstances being audited can be understood by auditors by utilizing knowledge, which enables more targeted planning and implementation of procedures, especially in the disclosure of fraud (Masnur et al., 2023). Auditors who have knowledge related to specific tasks will find it easier to carry out their duties and responsibilities as auditors, such as identifying the context and understanding the internal circumstances being audited, so that more effective and targeted planning and implementation of procedures can be created.

According to research conducted by Muzdalifah & Syamsu (2020) and Ardiansyah et al. (2024), task-specific knowledge has a positive and significant impact on auditors' ability to detect fraud. These results indicate that adequate specific knowledge in an auditor will make it easier for them to detect fraud signals. Auditors' knowledge is not only acquired through formal education but also through experience gained during the audit process. The more audit cases handled and resolved, the greater the ability to conduct examinations.

Based on the above description, the following hypothesis can be formulated: **H2**: Task specific knowledge have a significant positive effect on auditors' ability to detect fraud.

Brainstorming

Statement of Auditing Standard No. 99, Consideration of Fraud in a Financial Statement Audit, explains that potential fraud can be identified by auditors by utilizing discussions or exchanges of opinions (brainstorming), and this standard requires auditors to hold discussions related to the possibility of fraud occurring throughout the entire audit process (Laksana & Achmad, 2020).

Various empirical findings indicate that the effectiveness of brainstorming in audit practice remains inconsistent. Conceptually, team brainstorming is seen as capable of generating higher-quality fraud detection ideas through the exchange of knowledge and perspectives (Tummler & Quick, 2024). However, a number of studies have actually found that group discussions do not always improve auditors' ability to detect fraud, and may even reduce the number of fraud indicators identified compared to individual analysis (Juliana et al., 2021). This condition indicates that brainstorming practices can potentially be ineffective if not managed adequately. This is supported by the research findings of Feiby & Mowilos (2025), which show that audit team brainstorming does not have a positive and significant effect on fraud detection, as brainstorming audit methods and procedures are considered not effective enough in detecting fraud. Contrary to the research findings of Tang & Karim (2019) and Chen et al. (2018), providing guidance such as brainstorming can help auditors detect fraud better than not having a brainstorming session before the audit (Feiby & Mowilos, 2025).

Based on the above description, the following hypothesis can be formulated: **H3**: Brainstorming have a significant negative effect on auditors' ability to detect fraud.

Data Analytics

In Initiative 6.1 established by the Indonesian Institute of Accountants (IAI) in 2019, professional accountants must improve their skills in information technology, such as data analysis, to help corporate clients cope with developments and advances in information technology and detect signs of fraud in financial statements. In line with this, auditors must understand technology and improve their performance of responsibilities, and implementing good data security will help reduce fraud (Prasetyo et al., 2024).

In research conducted by Prasetyo et al. (2024), it was proven that data analytics has a positive influence on detecting fraud. The use of data analytics also benefits auditors, such as making it easier to collect evidence, establish a large population, predict risks, and facilitate rapid data analysis. Contrary to the research conducted by Claudiastuti (2023) and Kamal et al. (2022), which found that data analytics as an information technology has a negative influence on the detection of internal fraud in a company.

Based on the above description, the following hypothesis can be formulated: **H4**: Data analytics have a significant positive effect on auditors' ability to detect fraud.

METHODOLOGY

This study employs a quantitative approach using a causal comparative research design to analyze the cause-and-effect relationships between independent variables—namely red flags, task-specific knowledge, brainstorming, and data analytics—and the dependent variable, namely the ability of auditors to detect fraud at the Riau Provincial Inspectorate. The research population comprised all 63 internal auditors of the Riau Provincial Inspectorate, and a census sampling technique was applied so that the entire population was included as the research sample. Primary data were collected through the distribution of structured questionnaires to all auditors as respondents, which were developed based on indicators adapted from previous studies and measured using a five-point Likert scale to assess respondents' levels of agreement with each statement. The collected data were then analyzed using multiple linear regression analysis with the assistance of IBM SPSS Statistics version 29.

RESULTS AND DISCUSSION

Table 1. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.Deviation
RED FLAGS	41	18.00	30.00	27.7805	2.48508
TASK SPECIFIC KNOWLEDGE	41	30.00	40.00	36.7317	2.77511
BRAINSTORMING	41	35.00	45.00	42.6585	2.75327
DATA ANALYTICS	41	55.00	80.00	69.2683	6.75287
AUDITOR'S ABILITY TO DETECT FRAUD	41	36.00	54.00	48.8049	3.67573

Based on the table 1 above, it can be concluded that the highest average value is in the data analytics variable at 69.26, while the lowest is in the red flags variable at 27.78. The highest standard deviation is in the data analytics variable at 6.752, and the lowest is in the red flags variable at 2.485.

Table 2. Validity Test

Variable	Statement Items	Table R Value	Calculated R Value	Description
Red Flags	X1-1	0,3081	0,730	VALID
	X1-2	0,3081	0,841	VALID
	X1-3	0,3081	0,613	VALID
	X1-4	0,3081	0,407	VALID
	X1-5	0,3081	0,784	VALID
	X1-6	0,3081	0,770	VALID
Task Specific Knowledge	X2-1	0,3081	0,533	VALID
	X2-2	0,3081	0,604	VALID
	X2-3	0,3081	0,543	VALID
	X2-4	0,3081	0,678	VALID
	X2-5	0,3081	0,642	VALID
	X2-6	0,3081	0,705	VALID
	X2-7	0,3081	0,706	VALID
	X2-8	0,3081	0,543	VALID
Brainstorming	X3-1	0,3081	0,619	VALID
	X3-2	0,3081	0,629	VALID
	X3-3	0,3081	0,534	VALID
	X3-4	0,3081	0,584	VALID
	X3-5	0,3081	0,537	VALID
	X3-6	0,3081	0,506	VALID
	X3-7	0,3081	0,621	VALID
	X3-8	0,3081	0,603	VALID
	X3-9	0,3081	0,553	VALID

Data Analytics	X4-1	0,3081	0,533	VALID
	X4-2	0,3081	0,512	VALID
	X4-3	0,3081	0,529	VALID
	X4-4	0,3081	0,533	VALID
	X4-5	0,3081	0,647	VALID
	X4-6	0,3081	0,599	VALID
	X4-7	0,3081	0,587	VALID
	X4-8	0,3081	0,608	VALID
	X4-9	0,3081	0,558	VALID
	X4-10	0,3081	0,538	VALID
	X4-11	0,3081	0,550	VALID
	X4-12	0,3081	0,594	VALID
	X4-13	0,3081	0,506	VALID
	X4-14	0,3081	0,516	VALID
	X4-15	0,3081	0,581	VALID
	X4-16	0,3081	0,601	VALID
Auditor's Ability To Detect Fraud	Y-1	0,3081	0,561	VALID
	Y-2	0,3081	0,502	VALID
	Y-3	0,3081	0,463	VALID
	Y-4	0,3081	0,375	VALID
	Y-5	0,3081	0,608	VALID
	Y-6	0,3081	0,345	VALID
	Y-7	0,3081	0,544	VALID
	Y-8	0,3081	0,445	VALID
	Y-9	0,3081	0,693	VALID
	Y-10	0,3081	0,548	VALID
	Y-11	0,3081	0,528	VALID

Table 2 shows that all items in the questionnaire have positive correlation coefficients greater than the table r. This means that the data obtained is valid and further data testing can be carried out.

Table 3: Result of the Kolmogorov-Smirnov One-Sample Normality Test

N			41
Normal Parameters[a.b]	Mean		.0000000
	Std.Deviation		1.52318607
Most Extreme Differences	Absolute		.134
	Positive		.113
	Negative		-.134
Test Statistic			.134
Asymp. Sig. (2-tailed)[c]			.063
Monte Cario Sig. (2-tailed)[d]	Sig.		.063
	99% Confidence Interval	Lower Bound	.057
		Upper Bound	.069

Based on the results of the one-sample Kolmogorov test, it can be concluded that the data are normally distributed. This conclusion is supported by the one-sample Kolmogorov-Smirnov test results, which show a value above the 5% confidence level, specifically 0.063 or 6.3%. These results indicate that the data follow a normal distribution. In addition, the normal plot graph can also be examined to confirm whether the data are normally distributed.

Table 4: Reliability Test Result

No	Variable	Cronbach's Alpha	Description
1.	Red Flags	0,792	Reliabel
2.	Task Specific Knowledge	0,768	Reliabel
3.	Brainstorming	0,740	Reliabel
4.	Data Analytics	0,864	Reliabel
5.	Auditor's Ability To Detect Fraud	0,716	Reliabel

The results demonstrate that all variables have Cronbach's alpha values larger than 0.60, as indicated in Table 3 above. This result implies that the questionnaire instrument used to assess the variables of red flags, task- specific knowledge, data analytics, brainstorming, and auditors' capacity to detect fraud is trustworthy and may be considered a legitimate assessment tool.

Figure 1: Normality Results - Normal Probability Plot

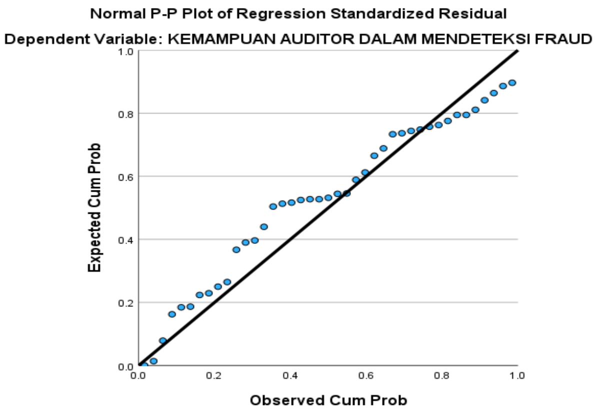
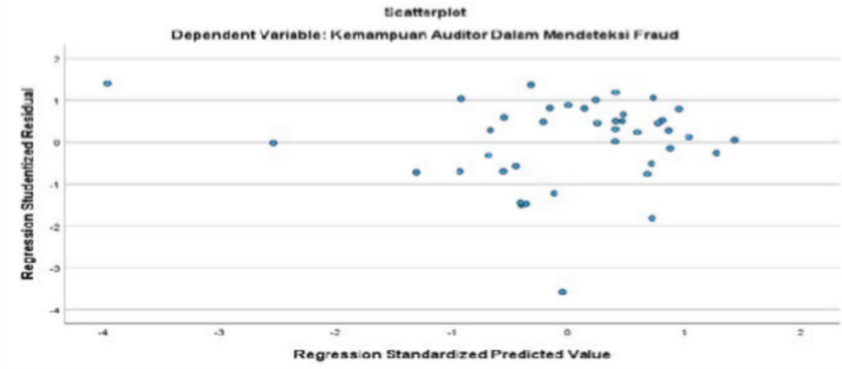


Figure 1 shows that there is a spread of points (data) around the diagonal line and that the direction of the diagonal line is followed by the spread of those points. This means that the assumption of normality can be fulfilled by a number of regression models in this study based on the analysis of the normal probability plot graph.

Figure 2: Heteroskedastisitas Test - Scatterplot Graph



The results of the heteroscedasticity test presented in Figure 2 indicate that the scatterplot between SRESID and ZPRED exhibits a dispersed pattern, with data points randomly distributed both above and below the zero value on the Y-axis. This pattern implies the absence of heteroscedasticity in the regression model, thereby confirming its suitability for predicting the variables of red flags, task-specific knowledge, brainstorming, and data analytics. Furthermore, the Glejser test can be employed to further assess the presence of heteroscedasticity. The test results are presented in Table 4.13, where a significance value greater than 0.05 indicates no heteroscedasticity, whereas a significance value less than 0.05 signifies the presence of heteroscedasticity. To corroborate these findings, an additional Glejser test was conducted as follows:

Table 5: Heteroskedastisitas Test With Uji Glejser

Model	Unstandardized B	Coeficients	Unstandardized Coeficients Beta	t	Sig
(constant)	-1.551	2.275		-.682	.500
RED FLAGS	-.069	.049	-.226	-1.394	.172
TASK SPECIFIC KNOWLEDGE	.055	.047	.200	1.167	.251
BRAINSTORMING	.000	.055	.001	.005	.966
DATA ANALYTICS	.032	.021	.286	1.537	.133

The findings of the glejser test in Table 5 above show that the probability for all independent variables is above the 5% significance level. This means that the occurrence of heteroscedasticity cannot be supported by the regression model.

Table 6: Multikolinearitas Test

Model	Unstandardized B	Coeficients	Unstandardized Coeficients Beta	t	sig	Collinearity Tolerance	Statistic VIF
(constant)	10.253	3.526		2.908	.006		
RED FLAGS	1.329	.077	.941	18.147	<.001	0.917	1.090
TASK SPECIFIC KNOWLEDGE	.181	.073	.137	2.487	.018	.817	1.224

BRAINSTORMING	-.289	.085	-.217	-3.397	.002	.606	1.651
DATA ANALYTICS	.081	.032	.148	2.491	.017	.698	1.433

Based on the test results in Table 6 above, the VIF values for all variables are <10. The VIF values for variables X1 (1.090), X2 (1.224), X3 (1.651), and X4 (1.433). This shows that there is no multicollinearity between the independent variables because all variable values are below 10. These results are supported by tolerance values that also show values >0.10. The tolerance values for variables X1 (0.919), X2 (0.817), X3 (0.606), and X4 (0.698) indicate that there is no multicollinearity in this study.

Table 7: Coefficient Determination Test (R^2)

According to the correlation interpretation guidelines, Table 7 shows that the R value is 0.955, or 95.5%. This figure falls within the "very strong correlation" category, which is defined as an R value between 0.80 and 1.00. This indicates that auditors' ability to detect fraud is positively influenced by red flags, task-specific knowledge, and data analytics. Conversely, auditors' ability to detect fraud is negatively influenced by brainstorming.

Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	.955[a]	.911	.901	1.154

The test of the coefficient of determination shows how much variance in the dependent variable is explained by the independent variable. Through the R-square value of the regression model, this test also measures the degree of influence that the independent variable exerts on the dependent variable. As shown in the table above, the R-square value is 0.901. This means that red flags, task-specific knowledge, brainstorming, and data analytics together influence 90.1% of fraud detection, while the remaining 9.9% is affected by other variables not examined in this study.

Table 8: Multiple Regression Test Results

Model	Unstandardized B	Coeficients	Unstandardized Coeficients Beta	t	sig
(constant)	10.253	3.526		2.908	.006
RED FLAGS	1.329	.077	.941	18.147	<.001
TASK SPECIFIC KNOWLEDGE	.181	.073	.137	2.487	.018
BRAINSTORMING	-.289	.085	-.217	-3.397	.002
DATA ANALYTICS	.081	.032	.148	2.491	.017

a. Dependent Variabel: KEMAMPUAN AUDITOR DALAM MENDETEKSI FRAUD

Based on Table above, the estimation model can be analysed as follows:

$$\mathbf{Y = 10{,}253 + 1{,}392X_1 + 0{,}181X_2 - 0{,}289X_3 + 0{,}081X_4 + e\ (1)}$$

Description:

- Y = Auditor's Ability to Detect Fraud
- X_1 = Red Flags
- X_2 = Task-Specific Knowledge
- X_3 = Brainstorming
- X_4 = Data Analytics
- a = Constant
- β_{1234} = Regression Coefficient
- e = Standard error

Auditor's ability to detect fraud when the independent variables of red flags, task- specific knowledge, brainstorming, and data analytics are zero. The regression coefficient for the red flags variable (β1) is +1.392, meaning that for every one-unit increase in red flags, the auditor's ability to detect fraud will increase by 1.392. The task-specific knowledge variable (β2) also has a positive effect, with a coefficient of 0.181, where a one-unit increase leads to an increase in fraud detection ability by 0.181. Conversely, the brainstorming variable (β3) with a coefficient of -0.289 indicates that an increase in brainstorming actually decreases auditors' ability to detect fraud by 0.289. Meanwhile, the data analytics variable (β4) with a coefficient of 0.081 has a positive, albeit small, effect on fraud detection ability. The standard error (e) represents a random variable that describes other factors affecting fraud detection capabilities but not included in this regression model.

Table 9: Hypothesis Test (Test Partial/ Test-t)

Model	Unstandardized B	Coeficients	Unstandardized Coeficients Beta	t	sig	Collinearity Tolerance	Statistic VIF
(constant)	10.253	3.526		2.908	.006		
RED FLAGS	1.329	.077	.941	18.147	<.001	0.917	1.090
TASK SPECIFIC KNOWLEDGE	.181	.073	.137	2.487	.018	.817	1.224
BRAINSTORMING	-.289	.085	-.217	-3.397	.002	.606	1.651
DATA ANALYTICS	.081	.032	.148	2.491	.017	.698	1.433

The findings of the hypothesis test indicate that the red flags variable significantly and positively influences the auditor's ability to detect fraud, as shown by a t-value of 18.147 > t-table 1.687 and significance <0.001; therefore, H1 is accepted. Likewise, the task-specific knowledge variable demonstrates a significant positive effect with a t-value of 2.487 > t-table 1.687 and significance of 0.018, leading to the acceptance of H2. In contrast, the brainstorming variable records a t-value of -3.397 < t-table 1.687 with a significance of 0.002, indicating that H3 is accepted. Finally, the data analytics variable provides a significant positive effect with a t-value of 2.491 > t-table 1.687 and significance of 0.017, resulting in the acceptance of H4. Based on these results, it can be concluded that increases in auditors' ability to detect fraud are positively affected by red flags, task specific knowledge, and data analytics, whereas brainstorming does not show a significant effect.

DISCUSSION

Research shows that the more red flags detected in an audit, the greater the likelihood of auditors in the Riau Provincial Inspectorate finding fraudulent practices. Red flags serve as an effective tool to enhance auditors' vigilance and sharpness in detecting fraud. Based on attribution theory, an auditor's ability is influenced by internal factors such as the auditor's understanding and perception in assessing red flags, as not all red flags necessarily indicate fraud, making the auditor's interpretation crucial in decision-making (Zakaria et al., 2023). The results of this study are consistent with research conducted by Ramadhani et al. (2024) and Achmad & Galib (2022), which states that red flags have a positive and significant effect on auditors' ability to detect fraud. This contrasts with research conducted by Desi Susilawati et al., (2022), which states that red flags have no significant effect on auditors' ability to detect fraud.

Auditors with adequate specialised knowledge, gained through education or experience, are more effective at recognising fraud signals and applying appropriate audit procedures. This knowledge is an important factor in improving fraud detection capabilities. Based on attribution theory, specific task knowledge helps auditors from the Riau Provincial Inspectorate understand and assess the causes of fraud, thereby improving the quality of fraud assessment and detection. This result is supported by the research of Ramadhani et al. (2024) and Muzdalifah & Syamsu, (2020) which shows a positive influence of specific task knowledge on auditors' ability to detect fraud.

The research results indicate that the more intensive the brainstorming sessions, the lower the ability of the Riau Provincial Inspectorate auditors to detect fraud, due to the dominance of opinions, lack of focus, groupthink, and overconfidence. This finding aligns with the research by Feiby & Mowilos, (2025), which states the negative influence of brainstorming on fraud detection. However, these results contradict some previous studies that stated brainstorming enhances creativity and collaboration in detecting fraud.

The use of data analytics in audits enhances auditors' ability to quickly and accurately identify unusual transaction patterns and potential fraud, making audit decisions more evidence-based. Integrating attribution theory and data analytics strengthens fraud detection by combining cognitive assessment and technological analysis. This finding aligns with the research by Anisa & Novita (2023) and Prasetyo et al. (2024), which states the positive influence of data analytics on auditors' ability to detect fraud, specifically at the Riau Provincial Inspectorate.

CONCLUSION

The research results that have been described in the previous chapter, the conclusion of this study is the analysis results show that red flags, task specific knowledge and data analytics have a significant positive effect on auditors' ability to detect fraud at the Riau Province Inspectorate Office. Whereas, the results of the brainstorming analysis have a significant negative effect on auditors' ability to detect fraud at the Riau Province Inspectorate Office. The analysis results indicate that red flags have a significant positive influence on auditors' ability to detect fraud at the Riau Province Inspectorate Office. This means that the more auditors understand and respond to the presence of red flags indicating fraudulent practices within an organisation, the more their vigilance and sharpness in identifying fraud indicators increase. Task-specific knowledge has a significant positive effect on auditors' ability to detect fraud at the Riau Province Inspectorate Office, this means that the more specific knowledge auditors have about the audit tasks they are performing, the more significantly it will contribute to their ability to detect indications of fraud. Thus, enhancing competence and gaining a deep understanding of audit characteristics and procedures are crucial factors that support the effectiveness of fraud detection by auditors.

The brainstorming analysis have a significant negative effect on auditors' ability to detect fraud at the Riau Province Inspectorate Office. This means that the higher the intensity of brainstorming in an audit, the more it can actually decrease the auditor's ability to detect fraud. This can happen because the discussion is dominated by certain opinions due to conflict avoidance (groupthink), a lack of focus on the main issue, and excessive confidence in the ideas that emerge (overconfidence), which eliminates scepticism. Finally, the lack of follow-up evaluation of the brainstorming results introduces bias into decision-making. Therefore, even though the goal is collaboration, such as improving audit quality, comprehensively identifying audit risks, and developing effective audit strategies, brainstorming can actually become an obstacle to increasing auditors' awareness of fraud. The results of the data analytics analysis have a positive and significant impact on the ability of auditors to detect fraud at the Riau Province Inspectorate Office. This means that the use of data analytics helps auditors at the Riau Province Inspectorate Office detect anomalies and fraud risks more effectively than traditional audits. This technology facilitates initial analysis, control evaluation, and risk assessment, and is beneficial in detecting bankruptcy and management fraud.

The researchers acknowledge that this study has limitations that are expected to provide direction for future research. The limitations of this study are this study was only conducted on auditors working at the Riau Provincial Inspectorate, so the findings cannot yet be generalised to auditors in other regions or institutions with different characteristics. The study used a quantitative approach with a questionnaire instrument, which has limitations in exploring in-depth information and allows for the emergence of subjectivity bias from respondents. This study only examined the variables of red flags, task-specific knowledge, brainstorming, and data analytics, and did not consider other factors that may also influence auditors' ability to detect fraud.

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