JURNAL
Riset Akuntansi dan Keuangan Indonesia
URL : http://journals.ums.ac.id/index.php/reaksi/index

Enhaching Fraud Detection Through Auditor Religiosity, Computer Assisted Audit Techniques, and Task Specific Knowledge: The Moderating Impact of Big Data on Auditors in BPKP, Sumatera Island

Betri[1], Ridho Hafidz[2]
[1,2]Program Studi Akuntansi, Fakultas Ekonomi dan Bisnis, Universitas Muhammadiyah Palembang
*betri.sirajuddin@gmail.com

Keywords:
Auditor Religiosity, Computer Assisted Audit Techniques, Task Specific Knowledge, Big Data, Fraud Detection

ABSTRACT
This study investigates the impact of Auditor Religiosity, Computer Assisted Audit Techniques (CAATs), and Task Specific Knowledge on Fraud Detection, with Big Data serving as a moderating variable. Conducted at the Representative Offices of the State Development Audit Agency in Sumatera, the associative research utilized primary data from 220 questionnaires, analyzed via Partial Least Square Structural Equation Modeling (PLS-SEM). Findings reveal that Auditor Religiosity and Task Specific Knowledge significantly influence Fraud Detection, while CAATs do not. Additionally, Big Data does not moderate the effects of Auditor Religiosity and Task Specific Knowledge on Fraud Detection (homologizer moderator). However, Big Data moderates (strengthens) the influence of Computer Assisted Audit Techniques on Fraud Detection (pure moderator).

p-ISSN:1411-6510
e-ISSN :2541-6111

INTRODUCTION

In this era of globalization, governmental institutionsfacesignificantchallengesinmaintaining their financial and operational integrity amidst increasingly complex economic and administrative dynamics. Uncertainty in public policies, demands for effective budget management, and the high need for accountability and transparency are primary focuses. Governments must ensure robust systems, both financially and in managerial practices, to prevent fraud amid financial instability. According to Kumaat (2011: 156), Fraud Detection can be described as a series of actions aimed at identifying early signs or strong indicators of potential fraudulent activities, while limiting opportunities for perpetrators. Religiosity, as discussed by Glock & Stark (1965) and Sari dkk., (2012), relates to individuals' levels of conception and commitment to their religion. Individuals with high religiosity tend to have strict moral standards and strong work ethics, making them better able to identify fraudulent actions. CAATs, as defined by Lin & Wang (2011), are tools, technologies, and software aiding auditors in control testing, data analysis, and auditing. The use of CAATs can improve audit efficiency and effectiveness, allowing auditors to conduct tests and analyze data more accurately and swiftly. Lala et al., (2014) suggest that auditors should no longer rely solely on conventional approaches in Fraud Detection, as failure to gather accurate audit evidence can significantly impact the occurrence of fraud. Task Specific Knowledge, according to Libby (1995), pertains to information relevant to audit tasks, aiding auditors in understanding the audited environment and internal conditions, thereby enhancing their assessment quality. Chen & Zhang (2014) explain that Big Data refers to large, complex data sets requiring advanced technology for analysis. Govindan et al., (2018) state that Big Data has the potential to enhance forensic audit functions in Fraud Detection.

Previous studies by Fadilah dkk., (2020) dan Bandiyono, (2023) find that religiosity affects Fraud Detection by auditors, consistent with the research by Suci dkk., (2022) which asserts the significant influence of religiosity on auditors' ability to detect fraud. However, research by Afriana (2019) suggests different results, indicating that religiosity does not influence internal auditors' ability to detect fraud. Findings from Olasanmi (2013), Atmaja (2016), Fauzi dkk., (2020), dan Samagaio & Diogo (2022) support the significant impact of CAATs on Fraud Detection. Research by Widuri & Gautama (2020) using a qualitative approach confirms that CAATs implementation plays a crucial role in the audit process and benefits Fraud Detection. Conversely, studies by Choirunnisa & Rufaedah (2022) dan Kamal (2022) suggest that information technology usage does not affect Fraud Detection by auditors. Studies by Yusrianti (2015), Betri & Kusumawaty (2019), Lembayung & Chomsatu (2021) indicate that Task Specific Knowledge influences Fraud Detection by auditors, supported by research by Johnson et al., (1993), Tirta & Sholihin (2004), Sari (2019), dan Muzdalifah & Syamsu (2020). Syahputra & Afnan (2020), Handoko dkk., (2022), Bandiyono (2023), dan Surono (2023) have shown that Big Data influences Fraud Detection. However, research conducted by Sembiring & Widuri (2023) yielded different results, indicating that Big Data does not affect Fraud Detection.

Religiosity plays a crucial role in enhancing auditor integrity during the audit process. Moreover, the utilization of Computer-Assisted Audit Techniques (CAATs) enables auditors to optimize the efficiency and effectiveness of audit procedures. This facilitates more accurate and swift data testing and analysis by auditors. Additionally, the pivotal role of Task Specific Knowledge cannot be overlooked, as it aids auditors in planning and executing audit procedures more systematically, thereby enhancing the quality of their assessments. Throughout the audit process, Task Specific Knowledge assists auditors in comprehending and resolving audit tasks, consequently improving the quality of their evaluations. Furthermore, Big Data exerts a significant influence, reinforcing the impact of auditor religiosity by providing broader access to relevant data. This enables auditors to track suspicious transactions that may contravene ethical or integrity principles. Moreover, in terms of CAATs utilization, Big Data enhances its effectiveness by enabling rapid and accurate analysis of large data volumes, thereby strengthening auditors' ability to identify suspicious patterns or anomalies. Lastly, Big Data also reinforces the influence of specific knowledge on audit tasks by providing broader access to relevant industry and business data. This allows auditors with in-depth knowledge of the audit context to identify suspicious patterns or trends that may go undetected manually.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Venkatesh et al., (2003) developed the Unified Theory of Acceptance and Use of Technology, which posits that technology usage is influenced by four main factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. This theory provides insights into how information technology can aid in Fraud Detection by auditors by understanding the factors that influence technology adoption. The concept of cognitive dissonance theory, first proposed by Festinger (1957), lays a crucial foundation for understanding communication dynamics and social influence. This theory highlights the inconsistency between cognitive elements, creating psychological discomfort. Muzdalifah & Syamsu (2020) underscore that cognitive dissonance theory impacts the change in auditor attitudes to predict intentions, aiming to reduce the arising inconsistency or dissonance. These cognitive factors guide auditors to ensure that the opinions they express after an audit align with the evidence they uncover during the examination process. The assumption of this theory is that individuals tend to seek consistency between beliefs, attitudes, and behaviors. Inconsistency among these components leads to cognitive dissonance, creating psychological discomfort. Thus, this theory provides insights into how Task Specific Knowledge can influence the Fraud Detection process conducted by auditors.

Attribution theory, first proposed by Heider (1958), addresses how individuals explain the causes of behavior and events. According to Fiske & Taylor (1991: 23), this theory discusses how social perception is used to make causal explanations about events. Its assumption is that individuals tend to explain behavior, whether their own or others', by attributing causes to internal or external factors, known as dispositional and situational attributions. Thus, this theory provides insights into how Auditor Religiosity can influence the Fraud Detection process. The way auditors interpret suspicious behavior will be influenced by religious values, which are dispositional attributions.

According to Betri (2022: 17), fraud is defined as an unlawful act that can be committed by individuals, both internal and external to an organization, with the motive of personal or group gain, ultimately resulting in direct losses to others. In efforts to enhance performance and reputation, organizations may resort to illegal actions, disregarding the consequences and parties affected by their actions. Detection, as per the KBBI Daring (2016), refers to the effort to discover and determine facts, assumptions, or the existence of something. Karyono (2013: 91) defines Fraud Detection as a process of identifying the occurrence of fraud, its perpetrators, victims, and the reasons behind the incidents.

According to Glock & Stark (1965), religiosity is defined as the level of conception about religion and the level of commitment in religious practices. Similarly, Sari dkk., (2012) explain that conception refers to an individual's understanding of their religious aspects, while commitment level relates to a comprehensive understanding in religious life. Hence, it can be concluded that individuals adopt different approaches to express and embody their religiosity. Individuals with high religiosity tend to exhibit strict moral standards and strong work ethics, thus being better able to identify fraudulent actions. Ghufron & Risnawati (2012) elucidate that religion has a binding nature, implying rules and responsibilities to be adhered to by its followers. Afriana (2019) explains that high religiosity can enhance an auditor's independence as they tend to uphold truth and justice steadfastly.

According to Lin & Wang (2011), CAATs are the utilization of various tools, technologies, and software to assist auditors in performing various audit tasks, including control testing, confirmation, financial statement data analysis, as well as continuous auditing and monitoring. As per Auditing Standard Section 327 in computerized accounting information systems environments, manual testing is impractical for auditors. Therefore, computer-assisted audit techniques, or CAATs, are necessary to enhance auditor performance and efficiency and improve Fraud Detection effectiveness. Braun & Davis (2003) emphasize that CAATs enrich the audit process through technology utilization, employing specialized software that enables auditors to achieve audit objectives more efficiently.

According to Libby (1995), Task Specific Knowledge refers to information stored in memory, including experiences, practical facts, and theoretical concepts related to audit tasks,

p-ISSN:1411-6510
e-ISSN :2541-6111

especially in evaluation and assessment processes. This information encompasses general and specific knowledge relevant to audit tasks. Sari (2019) states that Task Specific Knowledge assists auditors in understanding the audited environment and internal conditions, facilitating structured planning and execution of audit procedures. During audits, Task Specific Knowledge aids auditors in completing tasks more effectively, enhancing the quality of their assessments. Moyes & Hasan (1996) assert that the success of organizational audits in uncovering fraud, along with auditors' audit experience, is a significant element in potential Fraud Detection in each audit cycle and comprehensive risk assessment.

According to Sağiroğlu & Sinanc (2013), Big Data refers to a vast collection of data with complex and varied structures. Govindan et al., (2018) assert that Big Data has significant potential in enhancing forensic audit functions for Fraud Detection. Bandiyono (2023) cites one of the benefits of Big Data as its ability to assist companies in identifying fraud risks. Consequently, Big Data can support internal auditors in detecting fraud by expanding the coverage of essential data sources. This enables better analytical processes, ultimately enhancing the audit quality in identifying fraudulent activities.

The Influence of Auditor Religiosity on Fraud Detection

According to Glock & Stark (1965), religiosity is defined as the level of one's conception of their religion and the degree of commitment they have in religious practices. Similarly, Sari dkk., (2012) explain that the concept of conception refers to an individual's understanding of the aspects of their religion, while the level of commitment is related to a comprehensive understanding in religious life. Research conducted by Fadilah dkk., (2020) dan Bandiyono, (2023) indicate that there is an influence of religiosity on the detection of fraud by auditors. These findings align with a study by Suci dkk., (2022) which demonstrates that religiosity significantly affects auditors' ability to detect fraud. However, there is research with contrasting results to the aforementioned studies, such as the study conducted by Afriana (2019) which shows that religiosity does not influence the internal auditors' ability to detect fraud. Based on the above review, the researcher proposes a hypothesis:

H1a: Auditor Religiosity has a significant influence on Fraud Detection

The Influence of Computer Assisted Audit Techniques on Fraud Detection

CAATs, as defined by Perdana (2020: 176), are approaches that facilitate auditing processes using computers and related technologies. Zamzami dkk., (2021: 121) define CAATs as crucial tools that automate and audit audit data. The use of CAATs has transformed the auditing approach paradigm in Fraud Detection in the information technology era. CAATs provide auditors with the ability to delve deeper into data, analyze suspicious patterns and trends, and detect fraud indicators that are difficult to find manually. Research by Olasanmi (2013), Atmaja (2016), Fauzi dkk., (2020), dan Samagaio & Diogo (2022) proves that CAATs have a significant impact on Fraud Detection. This study, supported by research by Widuri & Gautama (2020), uses a qualitative approach and shows that the implementation of CAATs plays a crucial role in the audit process and provides benefits to audit results in detecting fraud. However, research by Choirunnisa & Rufaedah (2022) dan Kamal (2022) shows that the use of information technology has no effect on Fraud Detection by auditors. Based on this, auditors using CAATs as tools in the audit process will find it easier to identify existing anomalies, ultimately improving their examination results. Based on the above review, the researcher proposes a hypothesis:

H1b: Computer Assisted Audit Techniques has a significant influence on Fraud Detection

The Influence of Task Specific Knowledge on the Fraud Detection

Task Specific Knowledge, according to Libby (1995), refers to information stored in memory, including experience, practical facts, and theoretical concepts related to the performance of audit tasks, particularly in the evaluation and assessment process. This information encompasses general knowledge and more specific knowledge relevant to audit tasks. According to Sari (2019), Task Specific Knowledge can help auditors gain a deeper understanding of the audited environment and internal conditions, facilitating more structured audit planning and execution. During the audit process, Task Specific Knowledge assists auditors in understanding and completing audit tasks, enhancing the quality of their assessments. Research by Yusrianti (2015), Betri & Kusumawaty (2019), Lembayung & Chomsatu (2021) indicates that Task

Specific Knowledge influences Fraud Detection by auditors. This research is supported by studies by Johnson et al., (1993), Tirta & Sholihin (2004), Sari (2019), dan Muzdalifah & Syamsu (2020), which show that Task Specific Knowledge affects auditors' ability to detect fraud. Task Specific Knowledge enhances auditors' abilities during the audit process to detect fraud, facilitates more structured audit planning and execution, and assists auditors in understanding and completing audit tasks, thereby improving the quality of their assessments. Based on the above review, the researcher proposes a hypothesis:

H1c: Task Specific Knowledge has a significant influence on Fraud Detect

The Influence of Auditor Religiosity on Fraud Detection with Big Data As a Moderating Variable

Religiosity, as defined by Lestari & Indrawati (2017), reflects the internalization of religious values through adherence to and comprehension of religious teachings, manifested in everyday behavior. Additionally, Big Data, as elucidated by Sağiroğlu & Sinanc (2013), refers to vast collections of data characterized by complex and varied structures. Hipgrave (2013) underscores the potential of Big Data in expediting fraud investigation through data integration. Both Religiosity and Big Data influence the Fraud Detection process. Big data reinforces the influence of auditor religiosity by providing broader access to relevant data, enabling auditors to trace suspicious transactions that may contravene ethical or integrity principles. Previous research conducted by Syahputra & Afnan (2020), Handoko dkk., (2022), Bandiyono (2023), dan Surono (2023) has demonstrated that Big Data exerts an influence on Fraud Detection. The findings of this study indicate that the utilization of Big Data plays a significant role in the Fraud Detection process. However, contrary to the findings of research conducted by Sembiring & Widuri (2023), which suggest that Big Data does not influence Fraud Detection. Based on the above review, the researcher proposes a hypothesis:

H2a: Big Data Moderates the Influence of Auditor Religiosity on Fraud Detection

The Influence of Computer Assisted Audit Techniques on Fraud Detection with Big Data As a Moderating Variable

The utilization of Computer Assisted Audit Techniques (CAATs) has become crucial in enhancing the efficiency and effectiveness of audit processes. Braun & Davis (2003) elucidate that CAATs enrich the audit process through the utilization of specialized technology that empowers auditors to attain audit objectives. According to Zamzami dkk., (2021: 121), CAATs play a significant role in automating and auditing audit data. Conversely, Sağiroğlu & Sinanc (2013) refer to large, complex, and varied datasets. Hipgrave (2013) highlights the potential of Big Data in expediting fraud investigations through data integration. Big Data can moderate the influence of Computer Assisted Audit Techniques on Fraud Detection by strengthening or weakening the relationship between the two. CAATs are tools and techniques used by auditors to analyze data automatically and identify potential fraud or anomalies. In the context of big data, CAATs become more effective as they can process large volumes of data quickly and accurately. By harnessing big data, auditors can integrate CAATs into their audit processes to identify suspicious patterns or trends that may go undetected manually. Previous research conducted by Syahputra & Afnan (2020), Handoko dkk., (2022), Bandiyono (2023), dan Surono (2023) has shown that Big Data influences Fraud Detection. The findings of this research indicate that the utilization of Big Data plays a crucial role in the Fraud Detection process. However, contrary to the results of research conducted by Sembiring & Widuri (2023), which show that Big Data does not have an influence on Fraud Detection. Based on the above review, the researcher proposes a hypothesis:

H2b: Auditor Religiosity Moderates the Influence of Computer Assisted Audit Techniques on Fraud Detection

The Influence of Task Specific Knowledge on the Fraud Detection with Big Data As a Moderating Variable

Task Specific Knowledge, as elucidated by Sari (2019) and Libby (1995), refers to a specialized understanding of specific tasks, particularly within the context of audit tasks. This knowledge assists auditors in comprehending the environment and internal conditions of the audited entity, enabling them to plan and execute more directed audit procedures. Conversely, Sağiroğlu & Sinanc (2013) refer to a large dataset that exhibits complex and varied structures. Hipgrave (2013) highlights the potential of Big Data in expediting fraud

p-ISSN:1411-6510
e-ISSN :2541-6111

investigations through data integration. Big Data can moderate the influence of Task Specific Knowledge on Fraud Detection by reinforcing or attenuating the relationship between them. Task specific knowledge entails the auditor's understanding of the industry, business, or processes being audited. Big data can enhance the influence of task-specific knowledge by providing broader access to relevant industry and business data. Auditors with robust task-specific knowledge can utilize big data to identify patterns or trends in data that may indicate fraud. Previous research conducted by Syahputra & Afnan (2020), Handoko dkk., (2022), Bandiyono (2023), dan Surono (2023) has demonstrated that Big Data influences Fraud Detection. These research findings indicate that the utilization of Big Data plays a crucial role in the Fraud Detection process. However, in contrast to the findings of Sembiring & Widuri (2023), which indicate that Big Data has no influence on Fraud Detection. Based on the above review, the researcher proposes a hypothesis:

H2c: Big Data Moderates the Influence of Task Specific Knowledge on Fraud Detection

RESEARCH METHODS

This study employs an associative causal research design to investigate the impact of Auditor Religiosity, Computer Assisted Audit Techniques (CAATs), and Task Specific Knowledge on Fraud Detection, with Big Data acting as a moderating variable. Primary data were collected via questionnaires distributed to the Representative Offices of the State Development Audit Agency (BPKP) in Sumatera. The study's population consists of 876 auditors, with a sample size of 276 auditors determined using Slovin's formula at a 5% significance level, through probability sampling with simple random sampling methods.

The research adopts a Structural Equation Modeling (SEM) approach, utilizing Partial Least Squares (PLS) methodology via Smart PLS 4 software. This choice is made over Covariance-Based SEM (CB SEM) methods, such as AMOS or LISREL, due to several considerations. The dataset's non-normal distribution aligns with PLS SEM's robustness to deviations from normality, whereas CB SEM requires stricter assumptions. Additionally, the complex model, involving multiple variables and interaction effects, is better suited for PLS SEM, which can manage intricate models with latent variables and smaller sample sizes effectively. Although CB SEM could yield comparable results with larger datasets, PLS SEM's flexibility and efficiency align better with the research's objectives and constraints.

In summary, employing Smart PLS 4 for SEM analysis ensures rigorous evaluation of both the outer and inner models. This includes assessments of convergent validity, discriminant validity, and internal consistency reliability, as well as analyses of R Square, effect sizes (F Square), Q Square, and significance testing (t-tests and MRA). This methodological choice supports the robustness and validity of the study's findings, adhering to best practices in empirical auditing research.

RESULTS AND DISCUSSION

The characteristics of the respondents in this study consist of gender, age, highest education level, functional auditor position (JFA), and length of employment. There were 120 male respondents (54.55%) and 100 female respondents (45.45%). The majority of respondents were aged between 21 and 40 years, with the highest number in the age range of 31-40 years (34.09%). In terms of highest education level, most respondents had a D4/S1 educational background (68.18%), followed by D3 (20.91%) and S2 (10.91%). The most common functional auditor position was Auditor Pertama (29.09%) and Auditor Muda (28.64%). The majority of respondents (61.82%) had been employed for more than 10 years.

Table 1: Statistics Descriptive

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

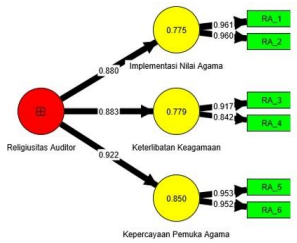
Source: Primary Data Processed, 2024

Based on the table above, the average score of respondents regarding the indicators of the Auditor Religiosity construct reaches 26.03, which significantly exceeds the theoretical median value of 18. These results indicate that the majority of respondents have a significant level of religiosity,

exceeding the median value used as a benchmark in the theoretical range. Similarly, the average score of respondents regarding the indicators of the Computer Assisted Audit Techniques construct reaches 70.32, which significantly exceeds the theoretical median value of 51. These results indicate that the majority of respondents have a much higher perception regarding the Computer Assisted Audit Techniques construct in the audit process compared to the theoretical median value. Furthermore, the average score of respondents regarding the indicators of the Task Specific Knowledge construct reaches 61.63, which significantly exceeds the theoretical median value of 42. This finding indicates that the majority of respondents have adequate knowledge to handle audit tasks. Additionally, the descriptive statistical test results indicate that the average score of respondents regarding the indicators of the Big Data construct reaches 68.92, which significantly exceeds the theoretical median value of 54. This indicates that the majority of respondents have a higher perception regarding the Big Data construct. Finally, the average score of respondents regarding the indicators of the Fraud Detection construct reaches 48.75, which significantly exceeds the theoretical median value of 33. This finding indicates that the majority of respondents have a high awareness and ability in Fraud Detection.

OUTER MODEL

The initial results of the outer model analysis include a comprehensive evaluation of the validity and reliability of constructs.



Construct	AVE
Implementasi Nilai Agama	0.923
Keterlibatan Kegiatan Keagamaan	0.775
Kepercayaan Pemuka Agama	0.907

Figure 1*: The Initial Measurement Model*

Source: Primary Data Processed, 2024

Based on the outer model above, it can be observed that all outer loading values of those indicators exceed the threshold of 0.708. Additionally, the Average Variance Extracted (AVE) values also surpass 0.50, indicating that all indicators meet the validity criteria. All outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values from the dimensional constructs to the Auditor Religiosity variable, all exceed 0.708. The AVE calculated for each dimensional construct and the Auditor Religiosity variable also exceed the threshold of 0.50, indicating convergent validity on the Auditor Religiosity variable and its manifestations.

Table 2*: Correlation Values Among Construct Dimensions, AVE, CR, and CA*

Indicator	INA	KPA	KK	*AVE*	*Composite Reliability*	*Cronbach's Alpha*
IIA	1			0.923	0.960	0.916
KPA	0.703	1		0.907	0.951	0.898
KK	0.646	0.758	1	0.775	0.873	0.715
SR of AVE	0.961	0.952	0.88			

Source: Primary Data Processed, 2024

Furthermore, the Fornell & Larcker (1981) criteria test revealed that each correlation between latent variables resulted in values lower than the square root of the Average Variance Extracted (AVE) of each related construct. Therefore, it is concluded that the Religiosity Auditor latent variable meets the criteria for discriminant validity.

Table 3*: Cross Loading*

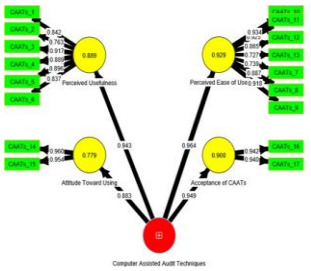
Indicator	INA	KKK	KPA	Description
RA_1	**0.961**	0.627	0.691	**Valid**
RA_2	**0.960**	0.613	0.659	**Valid**
RA_3	0.708	**0.917**	0.758	**Valid**
RA_4	0.386	**0.842**	0.554	**Valid**
RA_5	0.703	0.705	**0.953**	**Valid**
RA_6	0.635	0.740	**0.952**	**Valid**

Source: Primary Data Processed, 2024

The subsequent test, comparing the outer loading and cross-loading values, found that each outer loading value of the indicators onthe respective constructs consistently exceeded all cross-loading values from other constructs. This indicates that discriminant validity on the Religiosity Auditor variable has been met. The final test regarding internal consistency reliability showed that the Cronbach's Alpha values for each dimensional construct revealed numbers above 0.70, while the Composite Reliability values for each dimensional construct also exceeded 0.708. Therefore, it can be acknowledged that the Religiosity Auditor variable

p-ISSN:1411-6510
e-ISSN :2541-6111

and its manifestations demonstrate an adequate level of reliability. By evaluating the outer model measurement on the Religiosity Auditor latent variable, it can be concluded that all dimensional constructs and Religiosity Auditor variables show a level of validity and reliability that meets the rule of thumb criteria.



Construct	AVE
PU	0.738
PEU	0.709
ATU	0.915
AC	1

Figure 2: The Initial Measurement Model

Source: Primary Data Processed, 2024

Based on the above outer model, it can be observedthatallouterloadingvaluesoftheindicators exceed the threshold of 0.708. Additionally, the Average Variance Extracted (AVE) values also surpass 0.50, indicating that all indicators can be considered to meet the validity requirements. All outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values from the dimensional constructs to the CAATs variable, all exceed the threshold of 0.708. The calculated AVE for each dimensional construct and the CAATs variable also exceeds the threshold of 0.50, depicting the fulfillment of convergent validity on the CAATs variable and its manifestations.

Table 4: Correlation Values Among Construct Dimensions

Construct	AC	ATU	PEU	PU
AC	1			
ATU	0.896	1		
PEU	0.796	0.780	1	
PU	0.797	0.780	0.840	1
SR of AVE	1	0.957	0.842	0.859

Source: Primary Data Processed, 2024

Furthermore, in the Fornell & Larcker (1981) criteria test, there was a redundancy issue where the correlation value between indicators, thus it was concluded that the square root value of the AVE of the PEU construct was smaller than the correlation value between latent constructs, which was the most significant value of 0.860 < 0.901. This indicates that the Computer Assisted Audit Techniques latent variable does not meet the discriminant validity criteria. Therefore, the step taken to address this issue is to remove indicators that have high correlations with other indicators measuring different dimensions. After that, a revision was made, so there was a total of 1 model revision resulting in 2 tests. With the first revision model being the final model as convergent validity, discriminant validity, and internal consistency reliability have been met. Below are the details of the final model:

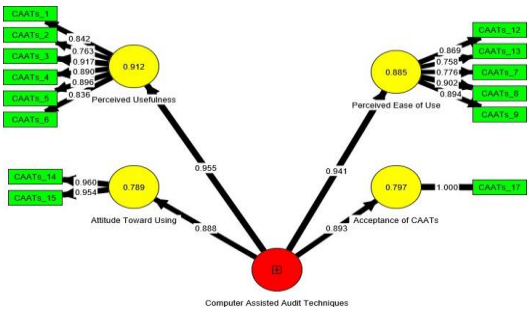


Figure 3*:* The Final Measurement Model

Source: Primary Data Processed, 2024

The results of the revision on the measurement instrument of CAATs variable yielded parameter estimations that attained validity and reliability levels meeting the rule of thumb standard. All outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values from the dimensional constructs to the CAATs variable, exceeded the threshold of 0.708.

Table 5: Correlation Values Among Construct Dimensions, AVE, CR, and CA

Construct	AC	ATU	PEU	PU	AVE	Composite Reliability	Cronbach's Alpha
AC	1				1	1	1
ATU	0.896	1			0.915	0.956	0.908
PEU	0.796	0.780	1		0.709	0.924	0.896
PU	0.797	0.780	0.840	1	0.738	0.944	0.928
SR of AVE	1	0.957	0.842	0.859			

Source: Primary Data Processed, 2024

Additionally, the Average Variance Extracted (AVE) values calculated for each dimensional construct and the CAATs variable also surpassed the threshold of 0.50, indicating that convergent validity on the CAATs variable and its manifestations has been fulfilled. Furthermore, in the Fornell & Larcker (1981) criteria test, it was revealed that each correlation between latent variables resulted in values lower than the square root of the Average Variance Extracted (AVE) of the respective related constructs. Therefore, it was concluded that the CAATs latent variable meets the criteria for discriminant validity.

Table 6: Cross Loading

Indicator	PU	PEU	ATU	AC	Description
CAATs_1	**0.842**	0.660	0.657	0.622	**Valid**
CAATs_2	**0.763**	0.645	0.525	0.543	**Valid**
CAATs_3	**0.917**	0.795	0.740	0.718	**Valid**
CAATs_4	**0.890**	0.738	0.720	0.784	**Valid**
CAATs_5	**0.896**	0.777	0.706	0.753	**Valid**
CAATs_6	**0.836**	0.699	0.653	0.665	**Valid**
CAATs_7	0.666	**0.776**	0.584	0.618	**Valid**
CAATs_8	0.749	**0.902**	0.695	0.698	**Valid**
CAATs_9	0.795	**0.894**	0.797	0.774	**Valid**
CAATs_12	0.702	**0.869**	0.681	0.705	**Valid**
CAATs_13	0.608	**0.758**	0.490	0.529	**Valid**
CAATs_14	0.772	0.784	**0.96**	0.867	**Valid**
CAATs_15	0.720	0.706	**0.954**	0.848	**Valid**
CAATs_17	0.797	0.796	0.896	**1**	**Valid**

Source: Primary Data Processed, 2024

The subsequent test involved comparing the outer loading values and cross-loading, where it was found that each indicator's outer loading value consistently surpassed all cross-loading values from other constructs. This indicates that discriminant validity on the CAATs variable has been met. The final test was internal consistency reliability. Referring to the data listed in the table, it can be observed that the Cronbach's Alpha values for each dimensional construct exceed 0.70, while the Composite Reliability values for each dimensional construct also exceed 0.708. Therefore, it can be acknowledged that the CAATs variable and its manifestations exhibit an adequate level of reliability. By evaluating the outer model measurement on the CAATs latent variable, which has been revised once, it can be concluded that all dimensional constructs and CAATs variables in the first revision demonstrate validity and reliability levels that meet the rule of thumb criteria.

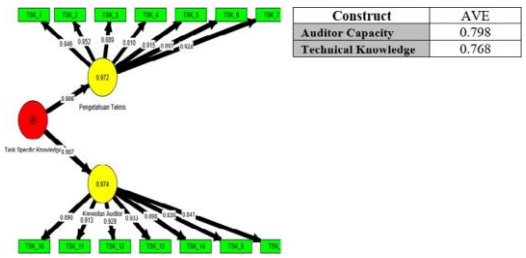


Figure 4: The Initial Measurement Model

Source: Primary Data Processed, 2024

p-ISSN:1411-6510
e-ISSN :2541-6111

Based on the outer model above, it can be observed that all the outer loading values of those indicators surpass the threshold of 0.708. Additionally, the Average Variance Extracted (AVE) values also exceed 0.50, indicating that all the indicators can be considered to meet the validity requirements. All the outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values from the dimensional constructs to the task specific knowledge variable, all exceed the value of 0.708. The calculated AVE for each dimensional construct and the task specific knowledge variable also surpass the threshold of 0.50, depicting the fulfillment of convergent validity on the task specific knowledge variable and its manifestations.

Table 7: Correlation Values Among Construct Dimensions

Construct	Auditor Capacity	Technical Knowledge
Auditor Capacity	1	
Technical knowledge	**0.946**	1
SR of AVE	0.893	0.876

Source: Primary Data Processed, 2024

Furthermore, in the Fornell & Larcker (1981) criteria test, there was redundancy issue where the correlation values between indicators. It was concluded that all correlation values between latent constructs were greater than the square root of the AVE of each related construct. This indicates that the Task Specific Knowledge latent variable does not meet the criteria for discriminant validity. Therefore, the step taken to address this issue was to remove indicators with high correlations with other indicators measuring different dimensions. After that, a revision was made, resulting in a total of 1 model revision, thus there were 2 rounds of testing. The first revision model is considered the final model because convergent validity, discriminant validity, and internal consistency reliability have been met. Below are the details of the final model:

The revision results on the instrument measuring the Task Specific Knowledge variable yielded parameter estimates that met the validity and reliability standards according to the rule of thumb. All outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values from the dimensional constructs to the Task Specific Knowledge variable, exceeded the threshold of 0.708.

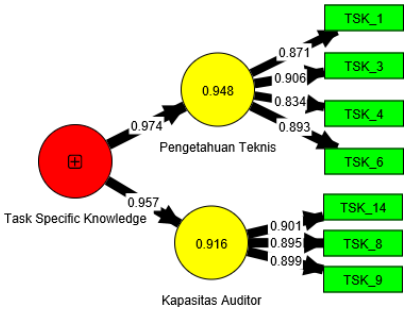


Figure 5: The Final Measurement Model

Source: Primary Data Processed, 2024

Table 8: Correlation Values Among Construct Dimensions, AVE, *CR, and CA*

Construct	AC	TK	AVE	Composite Reliability	Cronbach's Alpha
KA	1		0.806	0.926	0.88
PT	0.866	1	0.768	0.930	0.899
SR of AVE	0.898	0.876			

Source: Primary Data Processed, 2024

Additionally, the Average Variance Extracted (AVE) values calculated for each dimensional construct and the Task Specific Knowledge variable also exceeded the threshold of 0.50, indicating that convergent validity on the Task Specific Knowledge variable and its manifestations had been fulfilled. In the Fornell & Larcker (1981) criteria test, it was revealed that each correlation between latent variables produced values lower than the square root of the Average Variance Extracted (AVE) of each related construct. Therefore, it was concluded that the Task Specific Knowledge latent variable met the criteria for discriminant validity.

Table 9: Cross Loading

Indicator	Technical Knowledge	Auditor Capacity	Keterangan
TSK_1	**0.871**	0.764	**Valid**
TSK_3	**0.906**	0.831	**Valid**
TSK_4	**0.834**	0.663	**Valid**
TSK_6	**0.893**	0.767	**Valid**
TSK_8	0.806	**0.895**	**Valid**
TSK_9	0.749	**0.899**	**Valid**
TSK_14	0.776	**0.901**	**Valid**

Source: Primary Data Processed, 2024

In the subsequent test, comparing the outer loading and cross-loading values, it was found that each outer loading value of the indicators on the respective constructs consistently exceeded all cross-loading values from other constructs. This indicated that discriminant validity on the Task Specific Knowledge variable had been met. In the final test regarding internal consistency reliability, the data showed that the Cronbach's Alpha values for each dimensional construct revealed numbers above 0.70, while the Composite Reliability values for each dimensional construct also exceeded 0.708. Therefore, it can be concluded that the Task Specific Knowledge variable and its manifestations showed an adequate level of reliability. By evaluating the outer model measurement on the Task Specific Knowledge latent variable, which had been revised once, it can be concluded that all dimensional constructs and Task Specific Knowledge variables in the first revision showed a level of validity and reliability that met the rule of thumb criteria.

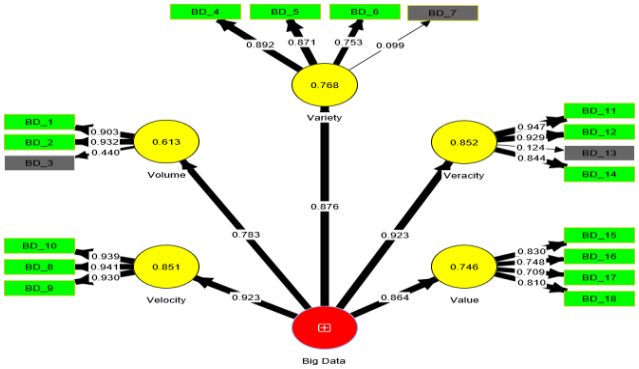


Figure 6: The Initial Measurement Model

Source: Primary Data Processed, 2024

Based on the outer model analysis above, it is concluded that some manifest variables have outer loading values below 0.708 (indicated in gray) on the Big Data variable, indicating the invalidity of some dimensions. This indicates the need for revision of the Big Data variable measurement model. Indicators BD_3, BD_7, and BD_13 are the cause of the invalidity of the Big Data variable. In the first revision stage, there was a redundancy issue where there was a significant correlation between indicator BD_15 (value) and BD_14 (veracity), with a correlation value of 0.811. This finding indicates redundancy between these indicators measuring different dimensions. The step taken to address this issue is to remove indicators that have high correlations with other indicators measuring different dimensions. After the revision, a second revision was performed, resulting in a total of three tests. The second revision model is considered the final model because convergent validity, discriminant validity, and internal consistency reliability have been met. Here are the details of the final model:

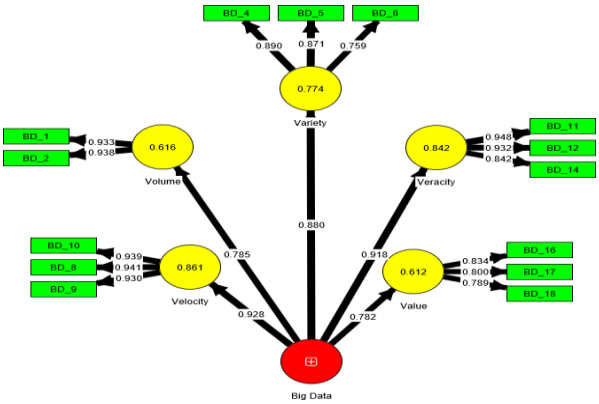


Figure 7: The Final Measurement Model

Source: Primary Data Processed, 2024

The results of the revision on the measurement instrument of the Big Data variable yielded parameter estimates that met the rule of thumb standards for validity and reliability. All outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values of the dimensional constructs to the Big Data variable, exceeded the threshold of 0.708.

Table 10: Correlation Values Among Construct Dimensions, AVE, CR, and CA

Construct	Value	Variety	Velocity	Veracity	Volume	AVE	Composite Reliability	Cronbach's Alpha
Value	1					0.653	0.849	0.753
Variety	0.587	1				0.709	0.879	0.792
Velocity	0.647	0.776	1			0.877	0.955	0.93
Veracity	0.682	0.733	0.841	1		0.825	0.934	0.893
Volume	0.537	0.684	0.644	0.624	1	0.875	0.933	0.857
SR of AVE	0.808	0.842	0.936	0.908	0.935			

Source: Primary Data Processed, 2024

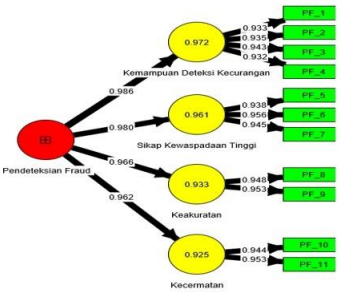
p-ISSN:1411-6510
e-ISSN :2541-6111

Additionally, the Average Variance Extracted (AVE) values calculated for each dimensional construct and the Big Data variable also exceeded the threshold of 0.50, indicating that convergent validity on the Big Data variable and its manifestations has been met. 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 the Big Data latent variable meets the criteria for discriminant validity.

Table 11: Cross Loading

Indicator	Volume	*Variety*	*Variety*	*Veracity*	*Value*	Description
BD_1	**0.933**	0.609	0.570	0.569	0.534	**Valid**
BD_2	**0.938**	0.670	0.634	0.598	0.473	**Valid**
BD_4	0.635	**0.890**	0.676	0.652	0.539	**Valid**
BD_5	0.584	**0.871**	0.675	0.676	0.501	**Valid**
BD_6	0.502	**0.759**	0.607	0.512	0.438	**Valid**
BD_8	0.669	0.780	**0.941**	0.767	0.603	**Valid**
BD_9	0.556	0.706	**0.930**	0.811	0.594	**Valid**
BD_10	0.583	0.692	**0.939**	0.786	0.620	**Valid**
BD_11	0.587	0.718	0.824	**0.948**	0.633	**Valid**
BD_12	0.596	0.671	0.779	**0.932**	0.650	**Valid**
BD_14	0.513	0.603	0.682	**0.842**	0.573	**Valid**
BD_16	0.342	0.305	0.370	0.423	**0.834**	**Valid**
BD_17	0.354	0.304	0.336	0.372	**0.800**	**Valid**
BD_18	0.536	0.677	0.724	0.732	**0.789**	**Valid**

The next test involved comparing the outer loading values and cross loading values, which found that each indicator's outer loading value on the respective construct consistently exceeded all cross loading values from other constructs. This indicates that discriminant validity on the Big Data variable has been met. The final test was internal consistency reliability. Referring to the data listed in the table 4, it can be observed that the Cronbach's Alpha values for each dimensional construct reveal figures above 0.70, while the Composite Reliability values for each dimensional construct also show figures exceeding 0.708. Therefore, it can be acknowledged that the Big Data variable along with its manifestations demonstrate an adequate level of reliability. By evaluating the outer model measurement of the Big Data latent variable, which has been revised twice, it can be concluded that all dimensional constructs and the Big Data variable in the third revision exhibit levels of validity and reliability that meet the rule of thumb criteria.



Construct	AVE
KDK	0.875
SKT	0.896
KAk	0.903
KeCTan	0.900

Figure 8: The Initial Measurement Model
Source: Primary Data Processed, 2024

Based on the outer model above, it can be observed that all outer loading values of those indicators exceed the threshold of 0.708. Additionally, the Average Variance Extracted (AVE) values also surpass 0.50, indicating that all indicators meet the validity criteria. All outer loading values on the manifest variables to the dimensional constructs, as well as the outer loading values from the dimensional constructs to the Fraud Detection

variable, all exceed 0.708. The AVE calculated for each dimensional construct and the Fraud Detection variable also exceed the threshold of 0.50, indicating convergent validity on the Fraud Detection variable and its manifestations.

Table 12: Correlation Values Among Construct Dimensions

Construct	Kak	KeCTan	KDK	SKT
Kak	1			
KeCTan	0.904	1		
KDK	**0.935**	**0.937**	1	
SKT	0.941	0.925	**0.949**	1
SR of AVE	0.950	0.949	0.935	0.947

Source: Primary Data Processed, 2024

Furthermore, in the Fornell & Larcker (1981) criteria test, there was redundancy issue where the correlation values between indicators showed that the square root of the AVE of the KDK construct was smaller than the correlation values between latent constructs (SKT) which were significant, namely 0.935 < 0.949. Likewise, the square root of the AVE of the KDK construct was smaller than the correlation values between latent constructs (KeCTan) which were significant, namely 0.935 < 0.937. And the square root of the AVE of the KDK construct was equal to the correlation values between latent constructs (Kak), which is 0.935. This indicates that the Fraud Detection latent variable does not meet the criteria for discriminant validity. Therefore, the step taken to address this issue is to remove indicators that have high correlations with other indicators measuring different dimensions. After that, a revision was made, so there was a total of 1 revision to the model, resulting in 2 testing phases. The first revised model is considered as the final model because convergent validity, discriminant validity, and internal consistency reliability have been fulfilled. Below is the detail of the final model:

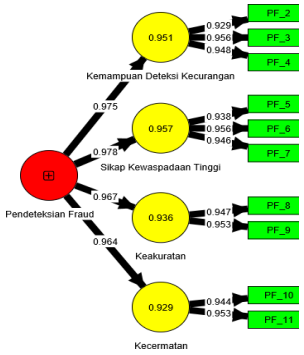


Figure 9: The Final Measurement Model

The results of the revision on the measurement instrument of Fraud Detection variable yielded parameter estimations that meet the levels of validity and reliability according to the rule of thumb standard. All outer loading values on the manifest variables to the dimensional constructs, and the outer loading values of the dimensional constructs to the Fraud Detection variable, exceed the threshold of 0.708.

Table 13: Correlation Values Among Construct Dimensions, AVE, *CR, and CA*

Indicator	Kak	KeCTan	KDK	SKT	AVE	Composite Reliability	Cronbach's Alpha
Kak	1				0.903	0.949	0.893
KeCTan	0.904	1			0.9	0.947	0.889
KDK	0.924	0.929	1		0.892	0.961	0.939
SKT	0.941	0.925	0.925	1	0.896	0.963	0.942
SR of AVE	0.95	0.949	0.944	0.947			

Source: Primary Data Processed, 2024

Additionally, the Average Variance Extracted (AVE) values calculated for each dimensional construct and the Fraud Detection variable also exceed the threshold of 0.50, indicating that convergent validity on the Fraud Detection variable and its manifestations has been fulfilled. In the Fornell & Larcker (1981) criteria test, it was revealed that each correlation between latent variables yields a value lower than the square root of the Average Variance Extracted (AVE) of each related construct. Therefore, it is concluded that the Fraud Detection latent variable meets the criteria for discriminant validity.

p-ISSN:1411-6510
e-ISSN :2541-6111

Table 14: Cross Loading

Indica-tor	KDK	SKT	KAk	Ke-CTan	Descrip-tion
PF_2	**0.929**	0.868	0.827	0.880	Valid
PF_3	**0.956**	0.889	0.918	0.881	Valid
PF_4	**0.948**	0.865	0.872	0.872	Valid
PF_5	0.854	**0.938**	0.878	0.863	Valid
PF_6	0.887	**0.956**	0.877	0.877	Valid
PF_7	0.886	**0.946**	0.918	0.887	Valid
PF_8	0.830	0.887	**0.947**	0.818	Valid
PF_9	0.924	0.902	**0.953**	0.899	Valid
PF_10	0.838	0.846	0.796	**0.944**	Valid
PF_11	0.922	0.907	0.915	**0.953**	Valid

Source: Primary Data Processed, 2024

The subsequent test involves comparing the outer loading values and cross-loading values, where it was found that each outer loading value of the indicators on the respective constructs consistently exceeds all cross-loading values from other constructs. This indicates that discriminant validity on the Fraud Detection variable has been fulfilled. The final test is internal consistency reliability. Referring to the data listed in the table, it can be observed that the Cronbach's Alpha values for each dimensional construct are above 0.70, while the Composite Reliability values for each dimensional construct also exceed 0.708. Therefore, it can be acknowledged that the Fraud Detection variable along with its manifestations demonstrate adequate levels of reliability. By evaluating the outer model measurement of the Fraud Detection latent variable, which has been revised once, it can be concluded that all dimensional constructs and the Fraud Detection variable in the first revision demonstrate levels of validity and reliability that meet the rule of thumb criteria.

INNER MODEL

R Square

The coefficient of determination (R Square Adjusted) test was conducted using Smart PLS 4, resulting in the following data:

Table 15: R Square

	R Square	*R Square Adjusted*
Fraud Detection	0.975	0.974

Source: Primary Data Processed, 2024

From the table above, 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 Auditor Religiosity (X1), Computer Assisted Audit Techniques (X2), Task Specific Knowledge (X3), and Big Data (X4) 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) and Hair et al., (2013), it can be concluded that this model is categorized as a strong model, with a value of 0.926 exceeding the threshold of 0.67 and 0.75, as recommended by these criteria.

Effect Size F^2

Hair et al., (2022: 209) explained that the effect size F2 facilitates the assessment of the contribution of an exogenous construct to the R2 value of the predictor latent variable. Values of F2 at 0.02, 0.15, and 0.35 indicate small, medium, or large effects, respectively, of a predictor construct on an endogenous construct. The F2 test was conducted using Smart PLS 4 with the following results:

Table 16: Effect Size F^2

	Fraud Detection
Auditor Religiosity	14.917
Computer Assisted Audit Techniques	0.000
Task Specific Knowledge	0.016
Big Data	0.000
AR_BD	0.004
CAATs_BD	0.019
TSK_BD	0.000

Source: Primary Data Processed, 2024

Based on the test results, the effect size f2 values are as follows: Auditor Religiosity (14.917, >0.35), Computer Assisted Audit Techniques (0.000, <0.02), and Task Specific Knowledge (0.016, >0.35). This indicates that X1 has a large effect size f2, while X2 and X3 do not have significant effect sizes f2. Additionally, the effect size f2 for the Big Data variable is 0.000 (<0.02), indicating that X4 does not have a significant effect size f2. Furthermore, the effect size f2 for the moderating

effects are as follows: RA_BD is 0.004 (<0.005) for M1, CAATs_BD is 0.019 (>0.01) for M2, and TSK_BD is 0.000 (<0.005) for M3. This shows that M1 and M3 do not have significant effect sizes f2, while M2 has a medium effect size f2.

Q^2 Predictive Relevance

Table 17: Q^2 Predictive Relevance

	RMSE	MAE	Q^2_*predict*
Fraud Detection	0.165	0.095	0.974

Source: Primary Data Processed, 2024

Based on the table above, it can be seen that the value of Q2 prediction reaches 0.974. This result indicates that the model has strong predictive relevance. A Q2 prediction value approaching 1 indicates that the model has high predictive ability.

Significance Test

Table 18: Path Coefficient, t-statistics significance, dan p-value

Konstrulk	Original Sample (O)	T Statistics	P *Values*	Result
RA -> PF	0.957	66.126	0.000	Ha1.a diterima
CAATs -> PF	0.003	0.160	0.436	Ha1.b ditolak
TSK -> PF	0.035	1.793	0.036	Ha1.c diterima
BD -> PF	0.001	0.094	0.462	-
RA_BD -> PF	-0.016	1.055	0.146	Ha2.a ditolak
CAATs_BD -> PF	0.022	2.362	0.009	Ha2.b diterima
TSK_BD -> PF	-0.001	0.088	0.465	Ha2.c ditolak

Source: Primary Data Processed, 2024

1. Based on the original sample value of 0.957 (95.7%), there is a positive and significant influence of Auditor Religiosity on Fraud Detection, as evidenced by the t-statistic value of 66.126, which is greater than the t-table value of 1.6518. Additionally, the obtained p-value of 0.000 indicates statistical significance (< 0.05). Therefore, based on the research hypothesis, H01.a is rejected and Ha1.a is accepted, indicating that Auditor Religiosity has a significant influence on Fraud Detection.
2. Based on the original sample value of 0.003 (0.3%), there is a positive but not significant influence of Computer Assisted Audit Techniques on Fraud Detection, as evidenced by the t-statistic value of 0.160, which is less than the t-table value of 1.6518. Additionally, the obtained p-value of 0.436 indicates no statistical significance (> 0.05). Therefore, based on the research hypothesis, H01.b is accepted and Ha1.b is rejected, indicating that Computer Assisted Audit Techniques do not have a significant influence on Fraud Detection.
3. Based on the original sample value of 0.035 (3.5%), there is a positive and significant influence of Task Specific Knowledge on Fraud Detection, as evidenced by the t-statistic value of 1.793, which is greater than the t-table value of 1.6518. Additionally, the obtained p-value of 0.036 indicates statistical significance (< 0.05). Therefore, based on the research hypothesis, H01.c is rejected and Ha1.c is accepted, indicating that Task Specific Knowledge has a significant influence on Fraud Detection.
4. Based on the original sample value of -0.016 (-1.6%), there is a negative influence of Big Data on the impact of Auditor Religiosity on Fraud Detection. However, this influence is not significant, as evidenced by the t-statistic value of 1.055, which is less than the t-table value of 1.6518. Additionally, the obtained p-value of 0.146 indicates no statistical significance (> 0.05). Therefore, based on the research hypothesis, H02.a is accepted and Ha2.a is rejected, indicating that Big Data does not moderate the influence of Auditor Religiosity on Fraud Detection.
5. Based on the original sample value of 0.022 (2.2%), there is a positive and significant influence of Big Data on the impact of Computer Assisted Audit Techniques on Fraud Detection, as evidenced by the t-statistic value of 2.362, which is greater than the t-table value of 1.6518. Additionally, the obtained p-value of 0.009 indicates statistical significance (< 0.05). Therefore, based on the research hypothesis, H02.b is rejected and Ha2.b is accepted, indicating that Big Data

p-ISSN:1411-6510
e-ISSN :2541-6111

moderates the influence of Computer Assisted Audit Techniques on Fraud Detection.

6. Based on the original sample value of -0.001 (-0.1%), there is a negative influence of Auditor Religiosity on the impact of Task Specific Knowledge on Fraud Detection. However, this influence is not significant, as evidenced by the t-statistic value of 0.088, which is less than the t-table value of 1.6518. Additionally, the obtained p-value of 0.465 indicates no statistical significance (> 0.05). Therefore, based on the research hypothesis, H02.c is accepted and Ha2.c is rejected, indicating that Big Data does not moderate the influence of Task Specific Knowledge on Fraud Detection.

DISCUSSION

H1a: Auditor Religiosity has a significant influence on Fraud Detection

Based on the data analysis, it is confirmed that Auditor Religiosity has a significant influence on Fraud Detection. Attribution theory, proposed by Heider (1958), is used as the framework to explain the research findings. This theory considers how individuals explain behavior and events, either through dispositional attributions (related to the individual) or situational attributions (related to the context). In this context, auditors with higher religiosity tend to have more positive dispositional attributions towards ethical behavior and are more likely to perceive unethical behavior as wrong, thereby increasing their likelihood of detecting fraud. In synthesis, attribution theory suggests that auditor religiosity influences the dispositional and situational attributions used by auditors in understanding behaviors and events associated with accounting fraud. Higher auditor religiosity can enhance more positive dispositional attributions and more accurate situational attributions, thereby improving auditors' ability to detect accounting fraud. Religious auditors may be more sensitive to indications of fraud because they are more inclined to believe that ethical behavior should always be maintained, regardless of whether the situation is supportive or not. Therefore, religiosity not only affects auditors' intrinsic motivation but also their assessment and reaction to potentially fraudulent situations. These findings are consistent with the research conducted by Fadilah dkk., (2020) and Bandiyono, (2023), which demonstrated the influence of religiosity on fraud detection by auditors. This research aligns with the study by Suci dkk., (2022), which showed that religiosity significantly impacts auditors' ability to detect fraud.

H1b: CAATs has a significant influence on Fraud Detection

Based on the data analysis, it is confirmed that CAATs (Computer Assisted Audit Techniques) do not have a significant influence on Fraud Detection. This is due to the fact that, although auditors have a positive perception of using Excel as an audit tool, the capabilities and complexity of Excel may not be sufficient to detect more sophisticated fraud. The Unified Theory of Acceptance and Use of Technology (UTAUT) is used as the framework to explain the relationship between the use of CAATs and fraud detection. UTAUT considers four main constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. In this context, although auditors have positive perceptions (high performance and effort expectancy), feel supported by colleagues (social influence), and have access to the necessary resources (facilitating conditions), the use of Excel remains inadequate for detecting more sophisticated fraud. This is due to Excel's limitations in analyzing highly complex data or detecting subtler fraud patterns, which often require more specialized and advanced audit tools. Furthermore, UTAUT helps explain that, although auditors perceive benefits and ease of use with Excel, and there is social support and adequate conditions, these factors do not automatically translate into increased effectiveness in fraud detection. This indicates that, beyond technology adoption, the quality and suitability of the audit tool for specific tasks such as fraud detection are also crucial. These findings are consistent with the research conducted by Choirunnisa & Rufaedah (2022) and Kamal (2022). However, studies by Olasanmi (2013), Atmaja (2016), Fauzi dkk., (2020), dan Samagaio & Diogo (2022), which show that CAATs do not have a significant impact on Fraud Detection, present different results. The study by Widuri & Gautama (2020), using a qualitative approach, also contrasts with this, indicating that the implementation of CAATs plays a crucial role in Fraud Detection.

H1c: Task Specific Knowledge has a significant influence on Fraud Detection

Based on the data analysis, it is confirmed that Task Specific Knowledge has a significant influence on Fraud Detection. This is attributed to two main factors: first, auditors with specialized knowledge in audit tasks tend to be more competent in identifying and analyzing signs of fraud. Second, in-depth knowledge of audit procedures and fraud detection techniques allows auditors to more accurately evaluate and interpret suspicious data. In the context of cognitive dissonance theory proposed by Festinger (1957), to reduce this dissonance, individuals tend to seek consistency through changes in their attitudes, beliefs, or behaviors. Auditors with specific knowledge of audit tasks have a strong knowledge base to detect fraud. When faced with information or data that is inconsistent with their understanding of how financial processes should occur, they experience cognitive dissonance. To reduce this dissonance, auditors are more likely to delve deeper and conduct more thorough examinations to identify the source of these inconsistencies, ultimately enhancing their ability to detect fraud. These findings support previous research by Yusrianti (2015), Betri & Kusumawaty (2019), Lembayung & Chomsatu (2021), which showed that Task Specific Knowledge influences Fraud Detection by auditors. This research is supported by studies by Johnson et al., (1993), Tirta & Sholihin (2004), Sari (2019), dan Muzdalifah & Syamsu (2020), and is consistent with cognitive dissonance theory.

H2a: Big Data Moderates the Influence of Auditor Religiosity on Fraud Detection

Based on the analysis results, it is confirmed that Big Data does not moderate the influence of Auditor Religiosity on Fraud Detection. This is attributed to two main factors: first, although Big Data offers significant potential to enhance data analysis capabilities, its effective use in fraud detection requires specialized tools, skills, and deep understanding that are not possessed by all auditors. Second, religiosity factors are more intrinsic and related to the personal values of auditors, which may not be directly influenced by sophisticated data analysis tools like Big Data. Attribution theory by Heider (1958) and UTAUT by Venkatesh et al., (2003) can help explain why Big Data does not moderate the influence of auditor religiosity on fraud detection. Religiosity is a dispositional factor that influences the personal values and ethics of auditors, while Big Data is a technical tool. Although Big Data can enhance data analysis capabilities, the religious values of auditors tend to influence how they perceive and react to fraud situations more than just the tools they use. Therefore, while Big Data can assist in fraud detection, the influence of auditor religiosity on fraud detection is more intrinsic and not significantly moderated by the use of Big Data.

H2b: Auditor Religiosity Moderates the Influence of CAATs on Fraud Detection

Based on the analysis results, it is confirmed that Big Data moderates and strengthens the influence of Computer Assisted Audit Techniques (CAATs) on Fraud Detection. This is attributed to two main factors: first, Big Data provides volume, variety, velocity, veracity, and value of data, enabling CAATs to analyze data on a much larger and more complex scale. Second, the integration of Big Data with CAATs allows auditors to detect patterns and anomalies that may not be visible with traditional audit techniques or smaller datasets. UTAUT by Venkatesh et al., (2003) can explain the relationship between these variables. With the existence of Big Data, auditors can conduct data analysis on a larger scale and at a faster pace. This enables CAATs to identify more complex and hidden fraud patterns that may not be detected with smaller datasets. The integration of Big Data and CAATs also enables auditors to perform predictive analysis and identify potential risks before fraud occurs. This enhances auditors' ability to proactively detect and prevent fraud. Thus, Big Data not only enhances the effectiveness of CAATs but also transforms auditors' approach from reactive to proactive in fraud detection.

H2c: Auditor Religiosity Moderates the Influence of Task Specific Knowledge on Fraud Detection

Based on the analysis results, it is confirmed that Big Data does not moderate the influence of Task Specific Knowledge on Fraud Detection. This is attributed to two main factors: first, although Big Data offers significant potential in data analysis, its effectiveness in detecting fraud largely depends on auditors' ability to utilize the data effectively. Auditors with specific knowledge about audit tasks may not yet be fully skilled or experienced in using

p-ISSN:1411-6510
e-ISSN :2541-6111

Big Data, thus the potential of this technology is not fully realized. Second, Task Specific Knowledge tends to focus more on technical skills and knowledge directly related to the audit process, which may not be fully enhanced solely by the presence of Big Data without adequate data analysis skills support. By utilizing UTAUT by Venkatesh et al., (2003) and cognitive dissonance theory by Festinger (1957) as the conceptual framework, we can understand that although auditors possess strong Task Specific Knowledge, the success of Big Data utilization in fraud detection largely depends on how comfortable and competent they feel in using the technology. Performance and effort expectations, social influence, as well as facilitating conditions all play crucial roles in determining the extent to which Big Data can influence fraud detection. Discomfort or lack of skills in using Big Data may hinder the potential of this technology, even though auditors have adequate technical knowledge.

CONCLUSION

Based on the data analysis, several key conclusions and practical recommendations regarding fraud detection in auditing emerge. The study confirms that Auditor Religiosity significantly influences Fraud Detection. Auditors with higher levels of religiosity are more likely to adhere to strong ethical standards, which enhances their ability to detect fraudulent activities. This finding emphasizes the importance of integrating auditors' personal values and beliefs into their professional conduct. Organizations should thus foster an environment that supports and respects auditors' ethical standards and personal values.

Conversely, Computer Assisted Audit Techniques (CAATs) do not have a significant influence on Fraud Detection in this study. Although CAATs are intended to improve audit efficiency and accuracy, their effectiveness in detecting fraud may be limited by factors such as data quality and auditors' proficiency with these tools. It is essential for organizations to ensure that auditors receive comprehensive training in CAATs and that these techniques are properly implemented to maximize their potential benefits.

Task-Specific Knowledge, however, does significantly impact Fraud Detection. Auditors with specialized knowledge in their audit tasks are better equipped to identify and analyze fraudulent activities. This underscores the necessity for ongoing professional development and targeted training programs to keep auditors updated on the latest fraud detection techniques and best practices.

The role of Big Data in this context is nuanced. The study finds that Big Data does not moderate the relationship between Auditor Religiosity and Fraud Detection or between Task-Specific Knowledge and Fraud Detection. However, Big Data does moderate the influence of CAATs on Fraud Detection. This suggests that while Big Data itself may not directly enhance fraud detection, its interaction with CAATs can be beneficial. Organizations should therefore focus on improving their capabilities to manage and analyze Big Data effectively, leveraging it to enhance the functionality of CAATs.

In conclusion, to enhance fraud detection capabilities, organizations should invest in comprehensive training and development programs to improve auditors' task-specific knowledge and ethical awareness. Additionally, adopting and effectively integrating CAATs into the audit process, along with creating an ethical work environment that aligns with auditors' personal values, can significantly boost fraud detection efforts. Addressing these recommendations will help organizations overcome challenges associated with Big Data and optimize the use of auditors' attributes and technological tools in their fraud detection practices.

REFERENCE

[1] V. G. Kumaat, Audit Internal. Jakarta: Penerbit Erlangga, 2011.

[2] C. Y. Glock and R. Stark, Religion and Society in Social Tension. USA: Rand McNally and Company, 1965.

[3] Y. Sari, Rd. A. Fajri S, and T. Syuriansyah, "Religiusitas pada Hijabers Community Bandung," Prosiding SNaPP2012: Sosial, Ekonomi, dan Humaniora, vol. 3, pp. 311–318, 2012.

[4] C. Lin and C. Wang, "A selection model for auditing," Industrial Management & Data, vol. 111, no. 5, pp. 776–790, 2011.

[5] S. Lala, M. Gupta, and R. Sharman, "Fraud Detection through Routine Use of CAATTs," 2014.

[6] R. Libby, The role of knowledge and memory in audit judgment. New York: Cambridge University Press, 1995.

[7] C. L. P. Chen and C.-Y. Zhang, "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data," Inf Sci (N Y), pp. 314–347, 2014.

[8] K. Govindan, T. C. E. Cheng, N. Mishra, and N. Shukla, "Big data analytics and application for logistics and supply chain management," Transp Res E Logist Transp Rev, pp. 343–349, 2018.

[9] N. Fadilah, I. K. Patra, and Rahmawati, "Pengaruh Religiusitas dan Rasionalisasi Terhadap Pendeteksian Kecurangan pada PT. PLN (Persero) ULP Kota Palopo," 2020.

[10] A. Bandiyono, "Fraud Detection: Religion In The Workplace Big Data Analytics," Jurnal Akuntansi, Jun. 2023.

[11] C. F. Suci, R. S. Putra, and R. Syaf, "The Effect of Red Flags, Auditor's Competence, Religiusity and Professional Skepticism on The Ability of Internal Auditors in Detecting Fraud," Digital Business Journal, vol. 1, no. 1, Jul. 2022.

[12] Afriana, "Pengaruh Pengalaman Kerja, Religiusitas dan Skeptisme Profesional Terhadap Kemampuan Auditor Internal dalam Mendeteksi Kecurangan (Studi Pada Kantor Inspektorat Kabupaten Buton Tengah dan Kabupaten Buton Selatan)," Jurnal Akademik Pendidikan Ekonomi, vol. 6, Nov. 2019.

[13] O. O. Olasanmi, "Computer Aided Audit Techniques and Fraud Detection," vol. 4, 2013.

[14] D. Atmaja, "Pengaruh Kompetensi, Profesionalisme, dan Pengalaman Audit Terhadap Kemampuan Auditor Badan Pemeriksa Keuangan (BPK) dalam Mendeteksi Fraud dengan Teknik Audit Berbantuan Komputer (TABK) Sebagai Variabel Moderasi," Media Riset Akuntansi, Auditing & Informasi, vol. 16, Apr. 2016.

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

[16] A. Samagaio and T. A. Diogo, "Effect of Computer Assisted Audit Tools on Corporate Sustainability," 2022.

[17] R. Widuri and Y. Gautama, "Computer-Assisted Audit Techniques (CAATs) for Financial Fraud Detection: A Qualitative Approach," 2020.

[18] A. Kamal, "Teknologi Informasi dan Skeptisme Profesional terhadap Fraud Detection Skills Auditor Internal Pemerintah," YUME : Journal of Management, pp. 295–313, 2022.

[19] R. Choirunnisa and Y. Rufaedah, "Pengaruh Kompetensi Auditor dan Pemanfaatan Teknologi Informasi Terhadap Pendeteksian Fraud," Jurnal Akuntansi Trisakti, vol. 9, no. 1, Feb. 2022.

p-ISSN:1411-6510
e-ISSN :2541-6111

[20] H. Yusrianti, "Pengaruh Pengalaman Audit, Beban Kerja, Task Specifi Knowledge Terhadap Pendeteksian Kecurangan Laporan Keuangan (Studi pada KAP di Sumater Bagian Selatan)," Jurnal Manajemen dan Bisnis Sriwijaya, vol. 13, 2015.

[21] Betri and M. Kusumawaty, "Pengaruh Pengalaman Audit, Beban Kerja, Task Specific Knowledge, Tipe Kepribadian Terhadap Pendeteksian Kecurangan Laporan Keuangan," 2019.

[22] H. D. Lembayung and Y. Chomsatu, "Determinan Pendeteksian Fraud Pada KAP di Surakarta," Jurnal Manajemen, Ekonomi, Keuangan dan Akuntansi (MEKA), pp. 253–260, 2021.

[23] P. E. Johnson, S. Grazioli, and Jamal. Karim, "Fraud Detection: Intentionality and Deception in Cognition," Accounting, Organizations and Society, vol. 18, no. 5, pp. 467–488, Jul. 1993.

[24] R. Tirta and M. Sholihin, "The Effects of Experience and Task-Specific Knowledge on Auditors' Performance in Assesing a Fraud Case," Jurnal Akuntansi dan Auditing Indonesia, vol. 8, no. 1, Jun. 2004.

[25] Sari, "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 dan Pengembangan Ekonomi Islam, vol. 3, no. 2, 2019.

[26] Muzdalifah and N. Syamsu, "Red Flags, Task Specific Knowledge dan Kemampuan Auditor dalam Mendeteksi Kecurangan," Jurnal Ekonomi Pembangunan, vol. 6, no. 2, pp. 92–101, 2020.

[27] B. E. Syahputra and A. Afnan, "Pendeteksian Fraud: Peran Big Data dan Audit Forensik," Jurnal Aset (Akuntansi Riset), vol. 12, no. 2, pp. 301–316, 2020.

[28] B. L. Handoko, A. Rosita, N. Ayuanda, and A. Y. Budiarto, "The Impact of Big Data Analytics and Forensic Audit in Fraud Detection," International Workshop on Computer Science and Engineering, vol. 12, 2022.

[29] Surono, "Dampak Pemanfaatan Big Data dan Audit Forensik dalam Pendeteksian Fraud," Jurnal Ilmiah Multidisiplin, vol. 1, no. 9, pp. 103–111, Oct. 2023.

[30] F. N. B. Sembiring and R. Widuri, "The Effect of Auditor Experience, Big Data and Forensic Audit as Mediating Variables on Fraud Detection," J Theor Appl Inf Technol, vol. 101, no. 6, 2023.

[31] V. Venkatesh, M. G. Morris, and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," MIS QUARTERLY, vol. 27, no. 3, pp. 425–478, Sep. 2003.

[32] L. Festinger, A theory of cognitive dissonance. Stanford University Press, 1957.

[33] F. Heider, The psychology of interpersonal relations. Hoboken: John Wiley & Sons Inc, 1958. doi: 10.1037/10628-000.

[34] S. T. Fiske and S. E. Taylor, Social Cognition, 2nd ed. Newyork: Mcgraw-Hill Book Company., 1991.

[35] Betri, Akuntansi Forensik dan Audit Investigatif, 1st ed. Palembang: NoerFikri, 2022.

[36] KBBI Daring, "'Deteksi,'" Badan Pengembangan dan Pembinaan Bahasa, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia.

[37] Karyono, Forensic Fraud. Yogjakarta: CV. Andi, 2013.

[38] M. N. Ghufron and Risnawati, Teori-teori Psikologi. Yogjakarta: Ar-Ruzz Media, 2012.

[39] SA Seksi 327.

[40] R. L. Braun and H. E. Davis, "Computer□assisted audit tools and techniques: analysis and perspectives," Managerial Auditing Journal, vol. 18, no. 9, pp. 725–731, 2003.

[41] G. D. Moyes and I. Hasan, "An empirical analysis of fraud detection likelihood," Managerial Auditing Journal, vol. 11, no. 3, 1996.

[42] Ş. Sağiroğlu and D. Sinanc, "Big data: A review," 2013.

[43] A. Perdana, Data Analytics: Keterampilan Teknik Akuntan dan Auditor di Era Digital. Madza Media, 2020.

[44] F. Zamzami, N. Duta Nusa, and F. I. Arifin, Sistem Informasi Akuntansi. UGM Press, 2021.

[45] D. Lestari and E. S. Indrawati, "Hubungan antara Religiusitas dengan Penyesuaian Diri pada Siswa dan Siswi Kelas VII Yayasan Pondok Pesantren Futuhiyyah Mranggen Kabupaten Demak," Jurnal empati, vol. 6, no. 14, pp. 307–312, 2017.

[46] S. Hipgrave, "Smarter fraud investigations with big data analytics," Network Security, vol. 2013, no. 12, Dec. 2013.

[47] C. Fornell and D. F. Larcker, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," Journal of Marketing Research, vol. 18, no. 1, p. 39, Feb. 1981, doi: 10.2307/3151312.

[48] D. T. Campbell and D. W. Fiske, "Convergent and discriminant validation by the multitrait-multimethod matrix.," Psychol Bull, vol. 56, no. 2, pp. 81–105, 1959, doi: 10.1037/h0046016.

[49] J. F. Hair, C. M. Ringle, and M. Sarstedt, "Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance," Long Range Plann, vol. 46, no. 1–2, pp. 1–12, Feb. 2013, doi: 10.1016/j.lrp.2013.01.001.

[50] D. J. Ketchen, "A Primer on Partial Least Squares Structural Equation Modeling," Long Range Plann, vol. 46, no. 1–2, pp. 184–185, Feb. 2013, doi: 10.1016/j.lrp.2013.01.002.

[51] K. A. Bollen, Structural Equations with Latent Variables. Wiley, 1989. doi: 10.1002/9781118619179.

[52] J. F. , Jr. Hair, G. T. M. Hult, C. M. , Ringle, and Marko. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd ed. United States of America: SAGE Publications, Inc., 2022.