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Redefining Fraud Detection: The Synergy Between Auditor Competency and AI-Powered Audit Analytics

Windy Permata Suyono, Eka Septariana Puspa, Surya Anugrah, Rio Firnanda
Fakultas Ekonomi dan Bisnis, Universitas Negeri Jakarta
[1]windypermata@unj.ac.id, [2]eka.septariana@unj.ac.id, [3]suryaanugrah@unj.ac.id, [4]riofirnanda2109@gmail.com

Abstrak .

This research investigates the impact of auditor competence on the effectiveness of fraud detection, with AI-driven audit analytics serving as a moderating factor. In the context of an increasingly digitalized economy, the complexity of financial fraud continues to evolve, posing challenges to conventional audit practices. The integration of Artificial Intelligence (AI) into auditing introduces advanced functionalities such as real-time data processing, anomaly identification, and predictive analysis. Nevertheless, the success of these AI applications depends substantially on the auditors' proficiency—particularly their technical expertise, critical thinking ability, and digital fluency. Employing a quantitative methodology with Partial Least Squares Structural Equation Modelling (PLS-SEM), this study collected responses from 100 Indonesian auditors familiar with digital audit technologies. The findings demonstrate a strong positive link between auditor competency and the ability to detect fraud effectively. Furthermore, the application of AI-powered audit analytics significantly enhances this relationship, positioning AI as a key facilitator in improving audit outcomes. This study not only adds to the expanding scholarship on digital auditing practices but also aligns with Sustainable Development Goal 9, which promotes innovation and technological advancement to foster institutional integrity. Additionally, it underscores the importance of comprehensive auditor development programs that combine technical training, ethical considerations, and digital tool integration to ensure responsible and effective use of AI in modern auditing.

Keywords : Auditor Competency, Fraud Detection, Artificial Intelligence, Audit Analytics, Digital Transformation

1. Introduction

In an era where financial fraud is becoming increasingly sophisticated, the role of auditors in detecting and preventing fraudulent activities has never been more critical. Traditional audit methods, while foundational, are no longer sufficient to address the complex nature of fraud schemes in today's data-driven business environment. As organizations transition into the digital economy, the demand for high-quality, real-time fraud detection mechanisms continues to rise (Appelbaum, Kogan, & Vasarhelyi, 2017).

Artificial Intelligence (AI) has become a game-changing innovation in the auditing domain, providing sophisticated analytical tools capable of identifying patterns and irregularities that may not be detectable through conventional human analysis. AI-powered audit analytics enable faster, more accurate, and predictive assessments of financial data, positioning it as a strategic tool in modern fraud detection (Kokina, Pachamanova, & Corbett, 2021). However, the effective use of these technologies' hinges not only on their availability but also on the competency of the auditors utilizing them.

Auditor competency encompassing technical knowledge, analytical skills, and familiarity with digital systems—plays a pivotal role in interpreting AI-driven insights and making informed judgments. When paired with robust AI analytics, competent auditors are more likely to detect fraud effectively (Kizil & Kocakulah, 2022). Despite this synergy, few empirical studies have investigated the interaction between human competency and AI systems in the context of fraud detection.

This research seeks to explore the effect of auditor competence on the effectiveness of fraud detection, with AI-based audit analytics functioning as a moderating factor in the relationship. The research contributes to the ongoing discourse on digital transformation in auditing and aligns with Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure), which emphasizes the importance of technological advancement in enhancing institutional quality and accountability (World Bank, 2023).

The integration of AI into the audit process not only enhances audit efficiency but also redefines the auditor's role from traditional inspection to strategic analysis. AI-powered audit analytics can process vast volumes of transactional data, identify irregularities, and generate risk indicators in real-time (Vasarhelyi, Kogan, & Tuttle, 2015). This capability allows organizations to shift from reactive to proactive fraud prevention. Nevertheless, without sufficient competency and understanding from auditors, the potential of AI cannot be fully realized. A technologically advanced audit tool in the hands of an unprepared auditor may lead to misinterpretation of data, ineffective audit conclusions, or even ethical dilemmas (IFAC, 2021).

In light of the aforementioned challenges, this research seeks to bridge a gap identified in prior studies by conducting an empirical analysis of how AI-driven audit analytics moderate the link between auditor capabilities and the effectiveness of fraud detection. By applying the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, the study evaluates the extent to which artificial intelligence can support and amplify human judgment in auditing. The expected outcomes are projected to offer valuable theoretical contributions to the literature on audit innovation, while also delivering actionable recommendations for practitioners, oversight agencies, and academic institutions working to equip auditors for the demands of digital transformation (OECD, 2020).

In addition, as the audit profession undergoes a significant digital transformation, there is a growing need to reevaluate the skillsets required of auditors to remain effective in a technologically complex environment. The integration of AI into audit procedures demands not only familiarity with emerging tools but also the ability to critically assess their outputs and implications. This shift highlights the importance of continuous learning and professional development tailored to digital competencies, including data literacy, system thinking, and ethical awareness in algorithm-based decision-making. As audit firms and regulators begin to incorporate AI into standard audit workflows, the synergy between technological innovation and human expertise becomes essential. Ensuring that auditors are adequately equipped to leverage AI tools responsibly and effectively is therefore not just a matter of operational efficiency, but a strategic imperative for enhancing trust, transparency, and accountability in the digital age.

2. Research Method

This study adopts a quantitative research design and utilizes Partial Least Squares Structural Equation modelling (PLS-SEM) to investigate the impact of auditor competence on fraud detection effectiveness, with AI-based audit analytics examined as a moderating factor. The PLS-SEM technique was selected due to its suitability in evaluating complex models involving latent variables and its robustness when used with small to medium sample sizes.

The research population comprises professional auditors operating in both public and private sector organizations within Indonesia. A purposive sampling strategy was employed to select respondents who met specific criteria: (1) experience in conducting audit work and (2) familiarity with, or prior use of, digital audit tools or AI-enabled systems. A total of 100 auditors based on Java Island were surveyed. This number satisfies the minimum sample size required for PLS-SEM analysis, in accordance with the 10-times rule that considers the number of measurement indicators used in the model.

Data were gathered through a structured online survey distributed via email and professional auditor networks. The questionnaire drew on established measurement items from previous academic sources and utilized a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The primary constructs analyzed in the study include Auditor Competency—reflecting skills such as technical knowledge, analytical thinking, and digital

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proficiency; Fraud Detection Effectiveness—representing auditors' capabilities in identifying, analyzing, and reporting fraudulent activity; and AI-Powered Audit Analytics—capturing perceptions of the relevance and application of AI in the auditing process.

The analysis was conducted using SmartPLS version 4.0, employing a two-stage process. The first stage involved evaluating the measurement model to verify the internal consistency, convergent validity, and discriminant validity of the constructs. The second stage assessed the structural model to test the hypothesized relationships, including the moderating effect of AI-powered analytics. Statistical significance of the path coefficients was determined through a bootstrapping procedure using 5,000 resamples.
Ethical standards were rigorously maintained during the entire research process. Respondents participated on a fully voluntary basis, with informed consent secured prior to data collection. They were assured that their identities would remain anonymous and their responses kept confidential. All collected information was solely utilized for academic and research-related purposes.

Table 1. Variable Operationalization

Variable	Operational Definition	Indicators	Source
Auditor Competency	The ability of auditors to carry out audit tasks professionally	a. Technical knowledge b. Analytical skills c. Digital literacy	Fitriana (2022)
Fraud Detection Effectiveness	The level of success in detecting and reporting fraudulent activities	a. Accuracy of detection b. Timeliness c. Completeness of reporting	ACFE (2021)
AI-Powered Audit Analytics *(Moderator)*	The use of AI-based technology to support the audit process	a. Perceived usefulness b. Ease of use c. Integration into audit processes	Yusof et al. (2023)

3. Result and Discussion

Result

Prior to analyzing the relationships among constructs within the structural model, it is essential to first assess the measurement model to verify that the indicators used for measuring latent variables possess adequate levels of validity and reliability. In this study, the measurement model was evaluated using the PLS algorithm, with parameters set accordingly. According to Heirs et al. (2022), the outer model is deemed acceptable if the outer loading values surpass 0.7. The results from the convergent validity assessment indicate that all outer loading scores exceed this threshold, confirming the validity of all indicators, as illustrated in Figure 1.

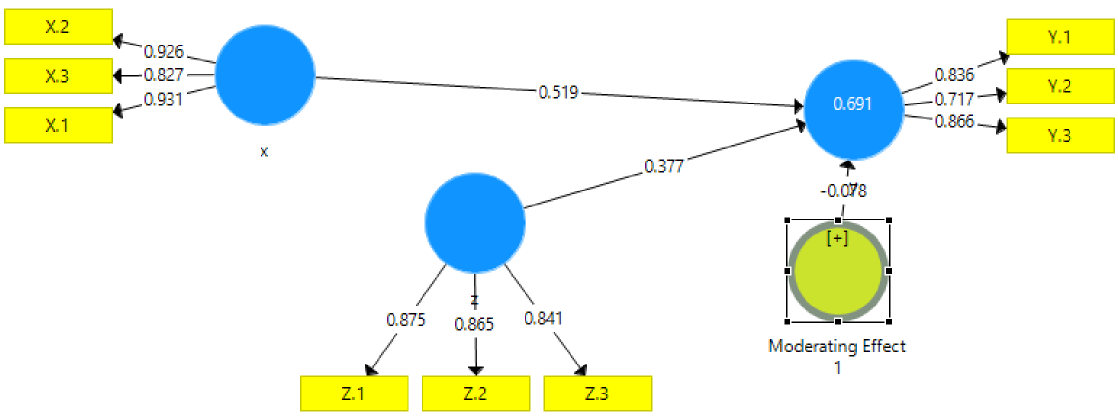

Fig. 1. Convergent Validity

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The next stage involves assessing discriminant validity, which examines how distinctly a construct differs from others within the model. This is evaluated through specific statistical techniques. As presented in Table 1, all heterotrait-monotrait (HTMT) values are below the 0.90 benchmark. In line with Heirs et al. (2022), HTMT values exceeding 0.90 suggest a lack of sufficient discriminant validity between constructs. Based on the results shown in Table 2, all constructs in this study report HTMT values below the 0.90 threshold, thereby confirming that each variable possesses satisfactory discriminant validity.

Table 2. Discrimant Validity

	AC	FD	AP
AC			
FD	0.899		
AP	0.737	0.889	

To confirm the reliability of each latent construct, this study evaluates both composite reliability and Cronbach's alpha. Based on the criteria outlined by Abdilah (2018), a construct is deemed to have satisfactory internal consistency when its composite reliability is 0.7 or above, and its Cronbach's alpha meets the minimum threshold of 0.6.

Table 3. Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	AVE	Decision
AC	0.875	0.924	0.802	Reliable
FD	0.733	0.750	0.654	Reliable
AP	0.825	0.895	0.740	Reliable

The internal consistency reliability results presented in Table 2 indicate that all latent constructs (AC, FD, and AP) demonstrate composite reliability values of 0.924, 0.750, and 0.895, respectively—all exceeding the acceptable threshold of 0.7. Additionally, their Cronbach's alpha values are 0.875, 0.733, and 0.825, respectively—all above the minimum standard of 0.6. These findings confirm that the three constructs are reliable and suitable for further analysis in the structural model evaluation stage.

The next step involves assessing the R-Square values to determine the explanatory power of the exogenous variables on the endogenous latent variable. According to Chin (1998), R-Square values can be categorized as substantial (0.67), moderate (0.33), or weak (0.19). As shown in Table 4, the R-Square value of 0.691 suggests that the exogenous constructs AC and FD jointly explain 69.1% of the variance in the endogenous construct AP.

Table 4. Value of R Square

	R Square	R Square Adjusted	Criteria
AI powered audit analytics (AP)	**0.691**	**0.682**	**Robust**

The overall model fit is determined by calculating the product of the average communalities and the R^2 value of the model. The Goodness of Fit (GoF) index ranges between 0 and 1, with thresholds commonly interpreted as 0.1 for weak fit, 0.25 for moderate fit, and 0.36 for strong fit. As presented in Table 5, the GoF value of 0.61 suggests that the model demonstrates a high level of predictive accuracy in capturing the influence of the exogenous variables AC and FD on the endogenous variable AP.

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Table 5. Goodness of Fitness Index

Latent Construct	AVE	R2
AC	0.802	
FD	0.654	
AP	0.740	
Average	0,732	0.691
GoF index Value	**0.711**	
	Large GoF	

Direct Effect

To examine the relationships between constructs within the model, Heirs et al. (2022) employed the bootstrapping technique with 5,000 resampling iterations. This method enables the estimation of path coefficients, standard errors (SE), p-values, t-values, and confidence intervals. Rather than relying solely on t-values and p-values to determine statistical significance, the Confidence Interval Bias Corrected (CIBC) approach was used to evaluate the upper and lower bounds. A relationship is considered statistically significant when the bootstrap confidence interval does not include zero.

Table 6. Direct Effect

	Original Sample	Standard Deviation	T Statistics	P Values
AC -> AP	0.519	0.078	6.676	0.000
FD -> AP	0.377	0.078	4.845	0.000

Table 6 outlines the outcomes of the direct effect analysis, derived from hypothesis testing using the SmartPLS software through the bootstrapping procedure. This technique is employed to determine the statistical relevance of each proposed relationship within the structural model by analyzing the t-values and p-values. Based on the accepted significance thresholds, a hypothesis is deemed valid if the t-statistic exceeds 1.9819 and the p-value is below 0.05, indicating a statistically significant relationship.

The findings are summarized as follows:

1. The relationship between audit competency and the application of AI-driven audit analytics exhibits a p-value of 0.000 and a t-value of 6.676, with an original path coefficient of 0.519. These indicators point to a strong and statistically meaningful positive association, thereby validating the first hypothesis.
2. Similarly, the impact of fraud detection effectiveness on AI-based audit analytics is confirmed by a p-value of 0.000 and a t-statistic of 4.845, along with an original sample coefficient of 0.377. This result affirms the second hypothesis, suggesting that higher effectiveness in detecting fraud correlates with increased integration of AI technologies in the audit process.

Together, these results underscore the importance of both auditor proficiency and the robustness of fraud detection systems in facilitating the adoption of AI-powered tools in auditing procedures.

Indirect Effect

After the direct effect hypothesis testing using bootstrapping test, the indirect effect with moderating method also was tested.

Table 7. Indirect Effect

	Original Sample	Standard Deviation	T Statistics	P Values
AC*FD-> AP	0.178	0.065	2.524	0.028

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Table 7 presents the outcomes of hypothesis testing for specific indirect effects, conducted using the bootstrapping method within the SmartPLS framework. This procedure assesses the statistical significance of mediating or moderating relationships among variables. The evaluation is guided by the standard criteria: a t-value exceeding 1.9819 and a p-value below 0.05 signify a statistically significant effect. The analysis yields the following result:

1. The indirect effect of audit competency on AI-powered audit analytics, mediated by fraud detection effectiveness, yields a *p*-value of 0.028 and a *t*-statistic of 2.524, with an original sample value of 0.178. These findings indicate a statistically significant mediating effect, confirming that fraud detection effectiveness strengthens the relationship between audit competency and the application of AI-based analytics. Therefore, the fifth hypothesis is supported.

This result highlights the important role of fraud detection effectiveness as a mediating factor that enhances the influence of auditor competencies in the successful adoption of AI-powered audit tools.

Discussion

The findings of this research validate that both auditor competence and the use of AI-powered audit analytics have a significant and positive impact on the effectiveness of fraud detection. These empirical results highlight the rising significance of synergistic interaction between human expertise and advanced technology within auditing practices, particularly as financial environments become more intricate and digitally driven. Firstly, the significant influence of auditor competency on fraud detection reinforces prior research suggesting that technical expertise, critical thinking, and digital fluency are crucial in identifying fraudulent activities. Auditors with a strong understanding of accounting systems, fraud schemes, and data analysis are better equipped to interpret financial irregularities and assess risk patterns accurately. This is consistent with the competency-based theory, which posits that individual capabilities are central to effective professional performance.

Secondly, the direct impact of AI-powered audit analytics on fraud detection effectiveness illustrates the transformative role of technology in modern auditing. Advanced analytics tools driven by artificial intelligence can process massive datasets, detect anomalies, and provide real-time insights—capabilities that surpass traditional manual audit techniques. These tools enhance the speed, scope, and accuracy of fraud detection procedures, enabling auditors to respond more proactively to red flags. This finding supports previous studies that highlight the effectiveness of AI in improving audit quality and fraud risk assessment (Yusof et al., 2023; Jameel et al., 2022).

Most notably, the moderating effect of AI-powered audit analytics on the relationship between auditor competency and fraud detection effectiveness was also found to be significant. This confirms the synergy between human judgment and machine intelligence. AI serves not as a replacement for auditors, but as an amplifier of their capabilities. Competent auditors are better positioned to leverage AI insights, interpret results meaningfully, and make strategic audit decisions. In turn, AI enhances the ability of skilled auditors to uncover fraud patterns that might otherwise go unnoticed. This synergy reflects the sociotechnical systems theory, emphasizing the mutual interdependence between people and technology.

These findings also align with Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure), which highlights the critical role of technological innovation in enhancing institutional efficiency and governance quality. Integrating AI capabilities with auditors' professional judgment allows audit firms to develop more resilient and responsive fraud detection mechanisms, thereby promoting organizational transparency and strengthening public trust in both governmental and private entities. xIn conclusion, this study highlights that fraud detection is no longer solely a matter of individual auditor skill or technological advancement, but rather a strategic convergence of both. Organizations are therefore encouraged to invest in upskilling their auditors while concurrently adopting AI-powered tools, ensuring a balanced and future-ready approach to combating fraud.

These findings also provide meaningful implications for audit education and professional development. Academic institutions and training providers need to redesign curricula and certification programs that emphasize the

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integration of digital audit tools, especially AI-powered systems, into traditional audit competencies. By fostering digital literacy alongside accounting and fraud examination skills, future auditors will be more agile in responding to emerging fraud risks. Furthermore, regulatory bodies may consider developing audit standards that support the responsible use of AI and ensure ethical data handling practices within the audit process.

Moreover, from an organizational perspective, the results suggest that investment in AI-based audit infrastructure should be aligned with strategies to develop human capital. Merely acquiring advanced audit analytics tools is not sufficient—auditors must be prepared, trained, and supported in using these tools to their full potential. Organizations that successfully cultivate this synergy between human expertise and machine capability will gain a competitive advantage in fraud prevention and governance. This alignment is particularly crucial in sectors with high fraud risk, such as government finance, procurement, and corporate financial reporting, where both accountability and technological capability are essential.

4. Conclusion

This study underscores the critical synergy between auditor competency and AI-powered audit analytics in enhancing fraud detection effectiveness. In the face of increasingly complex and data-driven fraud schemes, traditional audit approaches are no longer sufficient. Incorporating Artificial Intelligence into auditing offers a transformative potential by enabling real-time, precise, and forward-looking detection of fraudulent activities. However, the full potential of these technologies can only be realized when coupled with highly competent auditors who possess strong technical knowledge, analytical thinking, and digital literacy. The empirical findings of this study, analyzed using PLS-SEM, confirm that auditor competency significantly influences the effectiveness of fraud detection. Furthermore, AI-powered audit analytics acts as a moderating variable that amplifies this relationship, indicating that the presence of advanced technological tools strengthens the auditors' ability to detect fraud when they are adequately prepared to utilize them. This suggests that AI should not be seen as a replacement for human auditors, but as a complementary tool that enhances human judgment and efficiency. Moreover, the results highlight the necessity for audit firms and regulatory bodies to invest in continuous training programs that not only enhance technical audit skills but also cultivate digital fluency. As the audit landscape evolves, it is imperative that auditors remain agile, adaptable, and ethically responsible in leveraging AI tools. Institutions of higher education and professional certification bodies also play a vital role in integrating AI-related content into their curricula to prepare future auditors for technology-driven audit environments. In conclusion, this study adds valuable insight to the expanding discussion on the digital transformation of the auditing profession and aligns with the objectives of Sustainable Development Goal 9 (SDG 9) by encouraging technological innovation and the advancement of infrastructure. Future research could investigate additional moderating or mediating factors—such as organizational culture, regulatory frameworks, or ethical awareness—that may influence the successful adoption of AI in auditing. Overall, the findings offer a foundational perspective for both academic inquiry and practical application, emphasizing the importance of harmonizing human expertise with AI-driven analytics to enhance fraud detection and uphold organizational integrity.

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