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Evaluating financial audit efficiency: The role of artificial intelligence in proactive negligence mitigation

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Abstract: This study aims to provide empirical findings on the impact of AI implementation in improving audit efficiency, with a focus on fraud detection to reduce negligence in carrying out audit tasks. The focus of this study is to investigate the perceptions of auditors who have incorporated AI into their daily auditing work practices, comparing the quality of financial audits and fraud detection with those who have not utilized AI. The use of AI in auditing introduces a more efficient and proactive method to identify potential risks and errors. The research methodology involves distributing questionnaires to auditors with substantial experience in the audit industry. The questionnaires are designed to identify differences in audit quality and negligence mitigation perceptions between the use and non-use of AI. The findings of this study offer guidance for auditors in optimizing the benefits of AI to improve audit quality.
Keywords: *Artificial intelligence, Audit quality, Financial audit, Fraud detection.*

1. Introduction

In today's complex business environment, the efficiency of financial audits is crucial. Traditional auditing methods, though valuable, can be time-consuming, resource-heavy, and susceptible to human error. Artificial Intelligence (AI) offers a transformative solution by potentially revolutionizing the auditing process and reducing risks of negligence. As highlighted in a study by Goto [1] the main four accounting firms began integrating AI into their services in the 2010s, providing new insights for their R&D initiatives.

AI, as a flexible tool, enhances the auditor's performance by automating processes and reducing errors, although it requires significant technological expertise. This article will examine how AI can enhance audit accuracy and efficiency, compare the performance of auditors who use AI with those who do not, and address ethical and practical challenges associated with AI in auditing. Ultimately, the discussion aims to demonstrate how AI can transform auditing by promoting efficiency, reducing negligence risks, and helping auditors maintain compliance and build stakeholder trust in a digital age.

2. Literature Review

With advancements in information technology, auditors can analyze a large volume of financial data and transactions rather than examining just a small sample. This shift is further enhanced by new technologies such as Artificial Intelligence (AI) and Machine Learning (ML), which provide auditors with deeper insights into business operations and help assess risks more effectively [2]. To improve audit efficiency, auditors must stay informed about the latest technological developments.

Legitimacy theory, which addresses how companies behave in response to social and environmental issues, can be applied to understand the use of AI in financial audits [3]. According to this theory, audit firms adopt innovations like AI to enhance audit quality and credibility. Therefore, integrating AI into auditing practices is seen as a way for firms to boost their legitimacy and effectiveness.

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2.1. Financial Audit using Artificial Intelligence

Auditors play a critical role in assessing the reliability of financial statements by conducting audit procedures. As defined by Johnstone, et al. [4] auditing provides independent assurance on the accuracy of financial reports, thereby boosting stakeholder confidence. The objective is to ensure that financial statements are free from material misstatements [5].

Artificial Intelligence (AI) has unique characteristics, as discussed by Hasan [6] where machines or robots possess cognitive abilities to perceive, understand, and act within their environment to achieve specific goals. AI is designed to replicate human thinking and aid in decision-making and data analysis within organizations [7]. AI systems can adapt their behaviour, enhancing organizational efficiency and decision-making processes. Research on AI in auditing, such as that by Aitkazinov [8] shows its transformative potential. AI can improve audit efficiency, accuracy, and cost-effectiveness by analyzing large datasets and identifying complex patterns, thereby reducing negligence risks and saving time.

2.2. Audit Negligence

Auditors are responsible for ensuring that financial statements are free from material misstatements. Auditees expect auditors to perform with high-quality standards, but auditors sometimes fail to provide the correct opinion, impacting their liability. Liability judgments can be influenced by the outcomes for plaintiffs and various characteristics of the audit environment and process [9]. Audit negligence, a form of auditor liability, is categorized into ordinary negligence and gross negligence. Ordinary negligence occurs when someone fails to exercise reasonable care, resulting in harm. For example, if an auditor misses evidence of embezzlement that a prudent auditor would have found, this constitutes ordinary negligence. Professional standards require auditors to adhere to certain guidelines, and failing to do so can lead to negligence. Gross negligence is characterized by a lack of even minimal care or reckless disregard for truth. This occurs when an auditor issues an opinion on financial statements while ignoring professional standards, demonstrating such a lack of due diligence that it suggests an intention to deceive, even without direct evidence of intent [4].

2.3. Prior Studies & Hypothesis Development

The implementation of Artificial Intelligence (AI) in audit practices enhances auditors' performance and reputation by assisting in decision-making, though human involvement remains crucial for critical decisions that AI cannot handle [10]. Research shows a positive correlation between auditors' proficiency in using AI and their ability to meet client expectations, with auditors aged 40 and above often demonstrating greater AI proficiency than millennial auditors. AI also plays a significant role in accounting by automating repetitive tasks like data entry and analysis, allowing decision-makers to focus on tasks that require human judgment and ensuring that information is accurate and up to date [11].

2.4. Financial Audit Efficiency Using Artificial Intelligence for Negligence Mitigation

Financial audits, traditionally labor-intensive and reliant on sampling, are being transformed by Artificial Intelligence (AI), which enhances both quality and efficiency by automating tasks and detecting anomalies. Lindrianasari and Kuncoro [12] found in their study that the ability to work with Artificial Intelligence can provide a company with a Sustainable Competitive Advantage. This result is in line with research conducted by Hasan [6]. The findings of this study indicate that Artificial Intelligence capabilities will improve the quality of auditor work. As noted by Fedyk, et al. [13] audit firms, including the Big 4, are increasingly adopting AI to improve processes like fraud detection and error reduction. AI's ability to handle repetitive tasks and provide deeper insights allows auditors to focus more on critical judgments, significantly boosting audit efficiency [14]. Research by PwC and Deloitte [15] highlights AI's benefits, including reducing audit time by up to 40%, improving sample accuracy, automating tasks, and enhancing fraud detection and risk assessments. AI not only saves time and effort but also allows accounting professionals to concentrate on broader business objectives [16].

Based on the literature review explained above, the hypotheses of this research are:

H_1: The use of AI in financial audit has a positive impact on audit quality.

2.5. Artificial Intelligence for Identifying Potential Fraud

Artificial Intelligence (AI) has become a crucial tool for near real-time fraud detection by analyzing large datasets to identify trends and detect fraudulent transactions [17]. AI's impact is most significant in areas like fraud prevention, risk assessment, money laundering detection, bank secrecy, and cybersecurity, as it can handle diverse data formats and analyze leases, contracts, and network scans [13].

AI enhances fraud detection accuracy, reduces human error, and provides objective analyses, with the ability to predict fraud, not just detect it Supriadi [18]. Advanced analytics in AI allow for proactive fraud detection by examining client behaviour and communication patterns, identifying potential frauds like identity theft and phishing attempts before they result in losses. AI's adaptive learning algorithms continuously improve, staying ahead of evolving fraud schemes [19].

The integration of AI in fraud detection has transformed the ability to handle fraudulent schemes across industries, utilizing dynamic and adaptive methods to analyze large datasets and identify complex patterns and anomalies. Techniques range from deep learning architectures, such as neural networks, to machine learning algorithms involving supervised and unsupervised learning [20].

H_2: The use of AI in financial audit has a positive impact on fraud detection.

2.6. Millenials Proficiency Using AI to Detect Fraud

As technology advances, the integration of artificial intelligence (AI) in various fields, particularly fraud detection, has gained significant attention. Millennials, who have grown up in a digitally connected world, are seen as particularly skilled in utilizing AI technologies. AI encompasses computer programs that perform tasks requiring human intelligence, and millennials, characterized by their distinct ideals, experiences, and adaptability to technology, are inclined to incorporate AI into their daily lives [21].

AI has developed to solve problems, streamline tasks, and provide information rapidly, enhancing flexibility and problem-solving abilities [22]. It is widely used in risk management for predictive analytics, forecasting future events based on historical data [23]. With advancements in AI, accounting professionals are shifting focus to higher-value tasks such as analysis, decision-making, and strategy formulation [24]. Millennials' comfort with digital tools enables them to quickly adapt to these technological changes, enhancing their ability to integrate AI into workflows for improved fraud detection.

H_3: Millennials External Auditor are more proficient in using AI to detect fraud compared to non-millennial generation.

2.7. Millennials Using AI to Improve Quality of Audit

In an era of rapid technological advancements, the integration of artificial intelligence (AI) into auditing practices has become a significant development. Millennials, who are more adept at using digital tools, are particularly well-positioned to enhance audit quality through the application of AI, compared to their non-millennial counterparts [25].

AI helps millennials in their daily routines and satisfies their curiosity about its future development. Millennials use AI in specific situations, depending on their needs and preferences [26]. Research suggests that AI and other disruptive technologies are well-suited to improve the quality of financial reporting, making audits faster and more predictive [6].

It is recommended that AI be utilized in auditing firms for accounting and auditing tasks, as it aids in risk assessments, prompt reporting, and enhancing audit quality [27]. As AI continues to evolve, millennial external auditors, who are generally more familiar with digital tools, are expected to lead in utilizing these technologies to advance audit quality and adapt to the changing financial oversight landscape.

H_4: Millennials External Auditor who utilize AI can improve the quality of audit compared to non-millennial generation who do not use AI.

2.8. Educational Background to Detect Fraud Using Artificial Intelligence

In the evolving field of fraud detection, effectively utilizing artificial intelligence (AI) is essential. Individuals with higher educational qualifications are often better equipped to harness AI's advanced capabilities for fraud detection due to their enhanced analytical skills, deeper understanding of complex concepts, and greater familiarity with technological tools [28]. Postgraduate education, including degrees, certifications, and diplomas, enhances adaptability and competence, particularly in adopting new technologies like AI.

Technological advancements in AI are revolutionizing business activities and creating specific skill requirements, making adaptability to AI a crucial skill [29]. AI-driven fraud detection offers advantages such as increased efficiency, precision, large-scale data analysis, reduced false positives and negatives, and proactive fraud prevention through predictive analytics [30]. Individuals with higher education are generally more flexible and adept at integrating AI tools, enhancing their fraud detection strategies through the effective use of emerging technologies.

H5: Individuals with a higher educational background can use artificial intelligence more efficiently to detect fraud compared to those with a lower educational background.

2.9. Higher Education Impact to Improve Audit Quality with Artificial Intelligence

The integration of artificial intelligence (AI) in auditing underscores the importance of higher education in improving audit quality through AI adoption. Higher education provides individuals with advanced skills and knowledge essential for effectively utilizing AI technologies, fostering a deeper understanding of complex systems and enhancing adaptability to new technological advancements. Many pursue postgraduate education for personal, professional, and academic development, leading to significant knowledge expansion and personal growth [31].

This advanced education enables individuals to effectively apply AI tools, and as AI technologies gradually take over decision-making tasks, the role of technology in auditing will become even more significant. This shift presents an opportunity to enhance the quality of the auditor's report [32]. As technology continues to evolve, the importance of higher education in developing critical competencies for audit excellence becomes increasingly clear.

H6: Individuals with higher educational background can use AI to improve the quality of audit compared to those with a lower educational background.

3. Research Method

This research employs a quantitative approach, which involves generating numerical data and establishing cause-and-effect relationships between variables using mathematical, computational, and statistical methods [33]. Quantitative research is suitable for measuring the levels of perception, effectiveness, and responses to the use of artificial intelligence (AI) in financial auditing through structured and objective scales.

The study uses primary data, collected directly from external auditors at accounting firms in Indonesia who have integrated AI into their audit practices. Primary data is considered more reliable as it is analyzed directly from the source, enhancing confidence in decision-making [34]. The population of this study includes all external auditors in public accounting firms, while the sample comprises those who have employed AI in financial auditing. Purposive sampling is used to select respondents who meet specific criteria, ensuring that the sample accurately represents external auditors who use AI in their audit practices [35].

In this research, variables play a key role in defining the study's goals and outcomes. The independent variable (X) is the use of AI in financial auditing, including applications such as IBM Watson, Robotic Process Automation, GL.ai, and Natural Language Processing. The dependent variable (Y) is the audit quality, including time, cost, and the effectiveness of AI in fraud detection. Moderator variables include age and educational background, which can influence the relationship between the use of AI and audit quality.

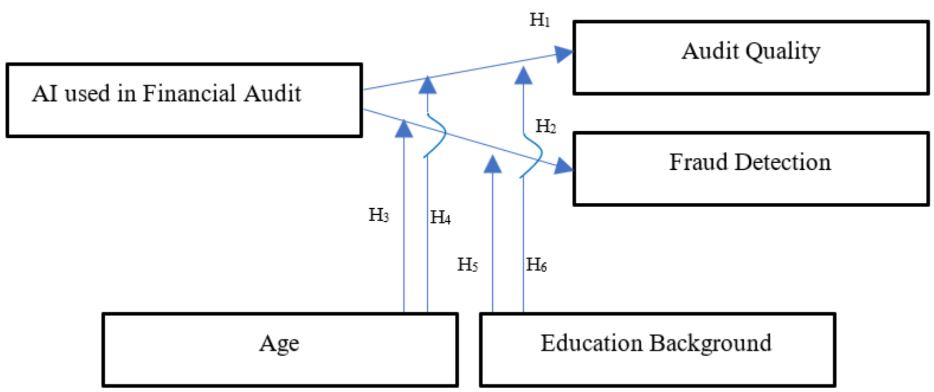

Figure 1.
Research Model.

Regression is a statistical tool used to analyze the relationship between a single outcome variable and multiple predictor variables. It is commonly used for forecasting, assessing trends, and understanding variable relationships [36]. In this research, the appropriate data analysis technique is inferential regression, as it aims to evaluate the impact of Artificial Intelligence (AI) on improving audit quality and fraud detection.

Using inferential regression allows researchers to determine if there is a significant relationship between the independent variable (AI use in financial auditing) and the dependent variable (audit quality and fraud detection). This technique also enables the assessment of AI's impact while controlling for other influencing factors, providing a deeper understanding of the extent to which AI implementation affects financial audit quality and fraud detection.

4. Results and Analysis

This chapter presents the results of the quantitative data analysis conducted using multiple linear regression. This method was chosen to examine the simultaneous effect of artificial intelligence (AI) on audit quality and fraud detection. Before performing the regression analysis, data from the questionnaires were tested for normality, and the validity and reliability of the instruments were assessed to ensure data quality. The study focuses on understanding how AI improves audit quality and fraud detection from the perspective of external auditors in public accounting firms in Indonesia. The data, sourced directly from 93 external auditors in various public accounting firms across Indonesia, was analyzed to test the research hypothesis. Table 2 shows the characteristics of the respondents in this study.

Table 1.
Model Summary.

R	R square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
0.809	0.655	0.643	0.72327	2.018

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Table 2.
Characteristics of the Respondents.

Age	Millennial	97.8%
	Non-Millennial	2.2%
Educational Background	Bachelor	88.2%
	Master	11.8%
Firms	Big 4	48.4%
	Big 10	35.5%
	Non-Big 4 & Big 10	16.1%
Position	Partner	2.2%
	Manager	7.5%
	Associate	47.3%
	Intern	43%

The reliability analysis using Cronbach's alpha showed coefficients of 0.86 for the independent variable (AI use), and 0.93 and 0.95 for the dependent variables (audit quality and fraud detection). These values exceed the recommended threshold of 0.6, indicating adequate internal consistency of the instruments [37].

Table 3.
Multiple Regression Analysis.

Model	**Unstandardized Coefficients**		**Standardized Coefficients Beta**	**t**	**Sig.**
	B	**Std. Error**			
(Constant)	12.305	1.349		9.124	0
Use of AI	0.369	0.029	0.788	12.63	0
Age	0.153	0.566	0.018	0.27	0.788
Educational Background	-0.656	0.254	-0.176	-2.581	0.011

Note: a. "Predictors: Constant, Edu Background, Use of AI, Age.
b. Dependent Variable: Audit Quality.

The coefficient of determination (R^2) measures how well the model predicts the outcome. For example, an R^2 of 0.20 means the model explains 20% of the variation in the result [38]. The regression coefficient is tested using the t-test to assess the significance of the association between the independent and dependent variables. This test compares the alternative hypothesis (that the regression coefficient has a significant effect) with the null hypothesis (that the coefficient has no significant effect) [39].

The R-squared value of 0.655 indicates that 65.5% of the variation in audit quality is explained by educational background, use of AI, and age, reflecting a moderately strong relationship between the independent variables and audit quality.

From table 3, the t-statistic for the use of AI is 12.630 ($p < .001$) showing a strong and statistically significant positive relationship with audit quality indicating that increased use of AI improves audit quality. For age, the t-statistic is 0.270 ($p = .788$), suggesting that age is not a significant predictor of audit quality in this model. The t-statistic for educational background is -2.581 ($p = .011$), indicating a statistically significant negative relationship implying that higher education levels are associated with decreased audit quality.

Table 4.
Multiple Regression Analysis.

R	R square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
0.794[a]	0.631	0.618	0.68319	2.098

Note: a. Predictors: Constant, Edu Background, Use of AI, Age
b. Dependent Variable: Fraud Detection

Table 5.
Multiple Regression Analysis.

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
(Constant)	11.322	1.274		8.887	0
Use of AI	0.339	0.028	0.791	12.262	0
Age	0.562	0.535	0.074	1.05	0.297
Educational Background	-0.146	0.24	-0.043	-0.61	0.544

Note: a. Predictors: Constant, Edu Background, Use of AI, Age
b. Dependent Variable: Fraud Detection

Table 4 show that R-squared value of 0.631 indicates that 63.1% of the variation in fraud detection is explained by age, educational background, and use of AI. This means these three variables account for a significant portion of the observed changes in fraud detection.

For the variable use of AI, the t-statistic is 12.262 with a significance level of 0.000, showing that AI significantly enhances fraud detection. Age has a t-statistic of 1.050 and a significance value of 0.297, suggesting that age does not significantly impact fraud detection. Similarly, educational background has a t-statistic of -0.610 with a significance value of 0.544, indicating that educational background does not significantly affect fraud detection (see table 5).

4.1. Correlational Analysis

Pearson correlation, often assessed through linear regression, measures the strength and direction of the relationship between two variables: one dependent and one independent. It helps evaluate how one variable influences the other [40].

Table 6.
Correlation Test.

			Use of AI	Audit Quality	Fraud Detection	Age	Edu Background
	Use of AI	Correlation	1.000	0.788	0.788	-0.052	-0.007
		Significance (2-tailed)	-	<0.001	<0.001	0.618	0.950
		df	0	91	91	91	91
	Audit Quality	Correlation	0.788	1.000	0.947	0.048	-0.188
		Significance (2-tailed)	<0.001	-	<0.001	0.646	0.070
		df	91	0	91	91	91
	Fraud Detection	Correlation	0.788	.947	1.000	0.050	-0.078
		Significance (2-tailed)	<.001	<.001	-	0.634	0.457
		df	91	91	0	91	91
	Age	Correlation	-0.052	0.048	0.050	1.000	-0.405
		Significance (2-tailed)	0.618	0.646	0.634	.	<1.000
		df	91	91	91	0	91
	Edu Background	Correlation	-0.007	-0.188	-0.078	-0.405	1.000
		Significance (2-tailed)	0.950	0.070	0.457	<0.001	-
		df	91	91	91	91	0
Age & Edu Background	Use of AI	Correlation	1.000	0.801	0.793		
		Significance (2-tailed)	-	<0.001	<0.001		
		df	0	89	89		
	Audit Quality	Correlation	0.801	1.000	0.954		
		Significance (2-tailed)	<0.001	-	<0.001		
		df	89	0	89		
	Fraud Detection	Correlation	0.793	0.954	1.000		
		Significance (2-tailed)	<0.001	<.001	-		
		df	89	89	0		

The strong positive correlation between the use of AI and audit quality (r = 0.788) indicates that increased reliance on AI significantly improves audit quality (see Table 6). Similarly, the strong positive correlation between AI use and fraud detection (r = 0.788) shows that AI tools are effective in identifying fraud, enhancing detection capabilities. The weak and statistically insignificant correlation between age and audit quality (r = 0.048) suggests that an auditor's age does not significantly impact audit quality. Likewise, the weak and non-significant correlation between age and fraud detection (r = 0.052) implies that age does not affect an auditor's ability to detect fraud.

The correlation between educational background and audit quality is weakly negative (r = -0.188), indicating a slight, non-significant decrease in audit quality with higher educational levels. Similarly, the correlation between educational background and fraud detection is weak and non-significant (r = -0.078), suggesting little impact of education on fraud detection capabilities.

Even after adjusting for age and educational background, the correlation between AI use and audit quality remains substantial ($r = 0.801$, $p < 0.001$), and the correlation between AI use and fraud detection remains notable ($r = 0.793$, $p < 0.001$). The relationship between fraud detection and audit quality strengthens ($r = 0.954$, $p < 0.001$) when adjusted for these variables, highlighting that AI's effectiveness in enhancing audit quality and fraud detection is consistent across different auditor demographics.

5. Conclusion

The study provides strong evidence that integrating AI into financial auditing significantly enhances audit quality. AI improves the thoroughness and accuracy of financial assessments and enhances fraud detection capabilities by analyzing complex data to identify patterns and anomalies indicative of fraudulent behavior. The findings reveal a robust positive correlation between AI use and audit quality, demonstrating that AI significantly boosts audit thoroughness and accuracy. Additionally, AI significantly improves the ability to detect fraudulent activities by identifying patterns and outliers in financial data.

The study found no significant difference in AI proficiency between millennial and non-millennial auditors, indicating that generational factors do not impact the effectiveness of AI tools for fraud detection. Instead, factors such as specific training, experience, and access to AI resources are likely more influential. Furthermore, there was no significant relationship between educational background and AI proficiency in improving audit quality. This suggests that while higher education may provide a foundation for understanding complex concepts, it does not necessarily translate into superior AI skills in the context of auditing. In summary, the benefits of AI in auditing are not contingent upon generational differences or educational background but are more dependent on the effective implementation and use of the technology.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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