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The Role Explainable Artificial Intelligence in Enhancing Auditor Judgment Quality in Indonesia

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ABSTRACT

This study explores the role of Explainable Artificial Intelligence (XAI) in improving the quality of auditors' decision-making in Indonesia. As AI systems become more prevalent in auditing practices, concerns regarding transparency and interpretability are increasingly relevant. XAI offers a solution by making AI-driven insights more understandable, thereby supporting professional judgment and reducing reliance on black-box systems. A quantitative approach was used, involving 100 professional auditors who completed a structured questionnaire based on a 5-point Likert scale. Data were analyzed using SPSS version 25. The findings revealed that XAI significantly influences auditors' decision-making quality, particularly in enhancing decision accuracy, risk assessment, and confidence in professional judgments. Regression analysis showed a strong positive relationship between XAI and decision-making quality, with XAI explaining 46.2% of the variance. These results highlight the importance of implementing explainable AI technologies to foster trust, accountability, and effectiveness in auditing practices across Indonesia.

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1. INTRODUCTION

The rapid development of Artificial Intelligence (AI) technology has significantly transformed various professional fields, including auditing, by enhancing efficiency, accuracy, and the ability to process large volumes of data. AI systems are increasingly employed to support auditors in detecting anomalies, analyzing financial data, and improving audit efficiency; however, their integration also raises critical concerns related to trust, transparency, and interpretability, especially when auditors rely heavily on automated recommendations in their decision-making processes [1], [2]. To address these challenges, Explainable Artificial Intelligence (XAI) has emerged as a crucial approach aimed at making AI decisions more understandable and transparent to human users, thereby fostering trust and accountability in auditing practices. XAI enhances the interpretability of AI models, allowing stakeholders to grasp the rationale behind automated outputs—an essential feature in high-accountability tasks such as fraud detection [1]. It also aids auditors and regulators in validating AI-generated recommendations to ensure regulatory compliance [2]. In practical applications, AI is used for anomaly detection, fraud prevention, revenue analysis, and risk assessment, significantly improving audit quality and operational efficiency [3], [4]. Leading audit firms like EY and PwC have adopted AI to automate repetitive tasks, minimize human error, and enhance analytical capabilities [4]. Technologies such as machine learning and natural language processing further enable auditors to concentrate on high-risk areas and conduct more comprehensive analyses s[3]. Nevertheless, implementing AI in auditing also entails challenges regarding data quality, algorithmic complexity, and adherence to regulatory standards [3], [4], and auditors must continually develop their competencies to effectively interpret AI outputs and maintain informed professional judgment [5].

In the context of auditing, Explainable Artificial Intelligence (XAI) offers substantial benefits by enabling auditors to comprehend the rationale behind AI-driven suggestions, thereby improving the quality of judgments and reducing the risk of blind reliance on opaque systems. The complexity of financial data and the ethical responsibility of auditors to make well-justified decisions underscore the importance of transparency, accountability, and interpretability in AI tools. XAI not only supports better decision-making but also enhances professional skepticism, regulatory compliance, and auditor accountability by offering interpretable models that align with financial standards and ethical expectations. XAI models provide transparency essential for compliance and regulatory decision-making in auditing by making AI decision processes understandable [2], [6]. These explanations help auditors identify and rectify biases or errors, thereby enhancing trust and accountability in AI systems [6], [7]. Moreover, XAI fosters a culture of professional skepticism by enabling auditors to critically evaluate AI-generated insights, which is vital in high-stakes domains like finance [1], [2]. Techniques such as rule-based systems and interpretable machine learning models are designed to meet the specific requirements of the financial domain, ensuring effective scrutiny of AI outputs [6], [8]. Additionally, XAI contributes to regulatory compliance by offering traceability and transparency in decision-making, which are critical for meeting standards like GAAP and IFRS [8], while also balancing technological innovation with ethical integrity [7].

In Indonesia, the integration of Artificial Intelligence (AI) and Explainable AI (XAI) in auditing is still at an early stage compared to more advanced economies, though local firms and regulators are beginning to explore its potential to enhance audit quality, efficiency, and fraud detection. While Big 4 firms are developing AI capabilities, smaller firms face financial, technical, and expertise-related barriers, leading to uneven adoption [9]. The country’s diverse professional backgrounds, regulatory frameworks, and technological readiness levels create implementation challenges that must be addressed. XAI offers clear benefits by automating routine tasks, supporting continuous auditing, and enabling auditors to focus on high-value functions like fraud detection [10]–[12]. However, its adoption is limited by skill gaps, ethical concerns, data security issues, and high customization costs[10], [11], [13], [14]. Addressing these issues requires accessible AI tools, clearer regulations, and targeted training to support smaller firms and reduce audit quality disparities [9]. A balanced approach that integrates advanced technology with professional judgment is key to optimizing AI use in Indonesia’s auditing landscape [14].

This study aims to empirically examine the role of XAI in improving the quality of auditors' decision-making in Indonesia. Specifically, it investigates the extent to which explainability in AI tools influences auditors’ ability to make accurate, confident, and well-informed decisions.

2. LITERATURE REVIEW

2.1 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) is a key advancement that addresses the need for transparency and interpretability in complex AI models, particularly in high-stakes fields like finance and auditing. By clarifying the "black-box" nature of AI, XAI enables users to understand and trust AI-driven decisions—crucial in auditing, where it helps explain why certain financial anomalies are flagged, allowing auditors to validate or challenge AI outputs. Techniques such as feature attribution, rule-based models, and surrogate models enhance model transparency and help identify potential flaws [15], [16]. In audit contexts, XAI supports ethical and regulatory compliance by making AI decisions more traceable and interpretable [17], [18]. Methods like LIME, Anchor, and SHAP, which are model-agnostic, further bridge the gap between complex AI processes and human understanding, improving decision-making and collaboration [17].

2.2 *AI in Auditing*

The integration of Artificial Intelligence (AI) in auditing offers significant potential to enhance audit efficiency and effectiveness by automating routine tasks, improving data analysis, and detecting anomalies. AI can reduce human error and free auditors to focus on complex issues [4], [19], while technologies like machine learning enable deeper analysis and better risk assessment [3]. AI systems also improve fraud detection by identifying irregularities more effectively than traditional methods [3], [4]. However, challenges remain, particularly regarding the transparency of AI algorithms, which often function as "black boxes" and hinder trust and decision-making [3], [19]. Additionally, auditors must acquire new technical skills, requiring substantial training and education [20], while regulatory and ethical concerns—such as data privacy and compliance—must also be addressed [3], [20]. Addressing these issues involves developing more interpretable algorithms [19], fostering interdisciplinary collaboration among auditors, AI experts, and regulators [4], and ensuring auditors continuously update their skills to effectively leverage emerging technologies [4], [20].

2.3 *The Role of XAI in Auditor Decision-Making*

Explainable AI (XAI) plays a crucial role in auditing by enhancing the transparency and interpretability of AI systems, which are increasingly used for complex decision-making tasks. XAI provides auditors with insights into how AI systems arrive at specific conclusions, supporting risk assessments, analytical reviews, and substantive testing, while allowing auditors to justify their decisions confidently and integrate AI tools more effectively into their workflows. By improving the interpretability of AI models, XAI enables auditors to understand decision-making processes—critical for accountability-driven tasks such as fraud detection and regulatory compliance [1], [2]. It also fosters trust and collaboration between human decision-makers and AI systems by addressing the opacity of traditional models [2], and contributes to improved risk assessment accuracy in domains like cybersecurity [21]. Practical implementations of XAI, such as explainability auditing methods used in image recognition, show how explanations can be evaluated for their relevance and strength, ensuring meaningful AI-driven decisions [22]. The ongoing development of interpretable models is essential for maintaining transparency, accountability, and fairness in AI applications across sectors, including finance and healthcare [23].

2.4 *Decision-Making Quality in Auditing*

Decision-making quality in auditing refers to the auditor's ability to make accurate, timely, and well-justified judgments, shaped by factors such as experience, regulatory standards, and cognitive tools like Explainable AI (XAI). High-quality decisions involve critical evaluation of evidence, professional skepticism, and integrity [24]. Experienced auditors are more capable of conducting objective and thorough audits

[25], while skepticism helps mitigate bias [26], [27]. Regulatory frameworks ensure adherence to professional standards [27], and tools like XAI support better interpretation of complex data [26]. Nonetheless, challenges such as variability in audit judgments and evolving definitions of audit quality reflect the dynamic nature of the auditing profession [27], [28].

2.5 *Technology Acceptance and Trust in AI*

The integration of AI tools in auditing is strongly influenced by the Technology Acceptance Model (TAM) and Trust Theory, where perceived usefulness and ease of use—as outlined by [29]—play a central role in shaping auditors' willingness to adopt new technologies. In the auditing context, the explainability of AI systems enhances these perceptions, making the tools more approachable and trustworthy. Trust, as emphasized by [30], is built on competence, integrity, and predictability—elements that are reinforced through explainable AI (XAI) [31], [32]User-friendly AI tools that clearly demonstrate benefits in terms of audit efficiency and effectiveness are more readily adopted [10], [33], [34]. Moreover, XAI significantly boosts perceived usefulness and ease of use, thereby fostering trust and encouraging adoption in auditing environments. While AI improves audit quality and enables continuous auditing, challenges such as high customization costs and the need for workflow adaptation remain [10]. Incorporating human-in-the-loop approaches, where auditors remain actively involved in AI-driven processes, can further strengthen trust and promote successful integration of AI in auditing practices [32].

2.6 *Previous Studies in Related Contexts*

Several empirical studies have examined the impact of AI and Explainable AI (XAI) on decision-making, showing that explanations significantly influence user acceptance and decision quality. [35] found that users were more likely to accept recommendations from decision aids when explanations were provided, while in the auditing domain, [36] reported that auditors using explainable AI models demonstrated higher accuracy and confidence compared to those relying on black-box systems. However, most existing research has focused on Western contexts, with limited exploration of XAI's impact on auditor behavior in emerging markets such as Indonesia. Despite the country's ongoing digital transformation and growing interest in AI within financial sectors, few studies have empirically tested the relationship between XAI and auditors' decision-making quality in the Indonesian context. Addressing this gap, the present study aims to provide empirical evidence on the role of XAI in enhancing auditors' decision-making through a structured quantitative approach tailored to Indonesia's unique professional and technological landscape.

3. RESEARCH METHODS

This study employs a quantitative approach to examine the role of Explainable Artificial Intelligence (XAI) in enhancing auditors' decision-making quality in Indonesia. A total of 100 professional auditors from public accounting firms, government audit bodies, and corporate internal audit units were selected using purposive sampling, focusing on those with at least one year of experience and exposure to AI tools. Data were collected through a structured questionnaire consisting of three sections: demographics, perceptions of XAI features (transparency, interpretability, usefulness), and self-assessed decision-making quality (confidence, accuracy, risk judgment, and justification), measured using a 5-point Likert scale.

The study investigates two main variables: XAI as the independent variable, and decision-making quality as the dependent variable. Validity was tested using Pearson correlation, and reliability through Cronbach's Alpha, with SPSS version 25.

Items with r-count values above the critical value were considered valid, and $\alpha > 0.70$ indicated good reliability.

Data analysis involved descriptive statistics, validity and reliability testing, normality testing, correlation analysis, simple linear regression, and t-tests, with a significance level of 0.05. This framework enabled the assessment of how perceived effectiveness of XAI influences auditors' decision-making quality within the Indonesian auditing context.

4. RESULTS AND DISCUSSION

4.1 *Descriptive Statistics*

Descriptive statistics were used to summarize respondents' perceptions of Explainable AI (XAI) and decision-making quality based on responses from 100 auditors. The average score for XAI features—including transparency, interpretability, and usefulness—was 4.12, reflecting a high positive perception of XAI among auditors. Meanwhile, the average score for decision-making quality was 4.21, indicating that auditors generally view their decision-making as strong, especially in terms of accuracy, confidence, and justification. These findings suggest that most auditors perceive XAI as a valuable tool that supports and enhances their professional judgment.

4.2 *Validity and Reliability Testing*

The validity test using Pearson correlation showed that all questionnaire items had correlation coefficients (r-count) greater than the r-table value of 0.195 at a 0.05 significance level, indicating that all items were valid. The reliability test results also confirmed the consistency of the instruments, with Cronbach's Alpha values of 0.821 for the XAI variable and 0.874 for decision-making quality—both exceeding the minimum threshold of 0.70—thereby affirming that the instruments used in this study are both valid and reliable.

4.3 *Normality Testing*

Kolmogorov-Smirnov test showed a significance value of 0.200 (> 0.05), indicating that the data were normally distributed and suitable for regression analysis.

4.4 *Simple Linear Regression Analysis*

The regression analysis was performed to examine the effect of Explainable Artificial Intelligence (XAI) on auditors' decision-making quality. The resulting regression equation was $Y = 2.135 + 0.501X$, indicating a positive relationship between XAI and decision-making quality. The R-squared value (R^2) was 0.462, which means that 46.2% of the variance in decision-making quality can be explained by XAI features such as transparency, interpretability, and usefulness.

The remaining 53.8% of the variance is likely influenced by other factors not included in the model, such as individual experience, organizational support, or regulatory environment. Furthermore, the ANOVA test yielded an F-value of 84.112 with a significance level of 0.000 ($p < 0.05$), confirming that the regression model is statistically significant and that XAI has a meaningful impact on auditors' decision-making quality.

4.5 *Hypothesis Testing*

The t-test results showed a t-count of 9.171 with a significance value (Sig. 2-tailed) of 0.000, which is less than 0.05, indicating that XAI has a significant positive effect on auditors' decision-making quality. Based on these findings, the research hypothesis is accepted.

4.6 *Discussion*

The results of this study support the hypothesis that Explainable Artificial Intelligence (XAI) positively influences the quality of auditors' decision-making. A significant beta coefficient of 0.501 indicates that improvements in XAI features—such as clarity, transparency, and interpretability—directly enhance auditors' ability to make more accurate, confident, and accountable decisions.

These findings are consistent with previous research, which shows that professionals are more likely to rely on AI recommendations when the rationale behind those decisions is clearly communicated, particularly in high-risk environments like auditing.

AI plays a growing role in auditing by automating tasks such as data collection, anomaly detection, and risk assessment, allowing auditors to shift their focus to high-value activities such as fraud detection [12]. The adoption of AI also brings benefits such as cost efficiency and improved audit accuracy, which are essential for enhancing overall audit quality and operational effectiveness [10], [20]. However, the "black box" nature of many AI algorithms remains a major challenge, as it can limit auditors' trust in AI outputs. XAI addresses this issue by making AI processes more transparent and interpretable [1], [19].

To ensure the effective use of AI tools, training and education are critical so that auditors can develop the necessary skills to understand and utilize AI technology appropriately [19], [20]. Explainable AI is especially vital in auditing because it enhances accountability and trust, enabling auditors to justify their decisions with confidence [1]. The integration of explainability layers within AI systems significantly improves the interpretability of AI-driven outputs, which is crucial in high-stakes decision-making environments such as auditing.

The relatively high R-squared value of 46.2% found in this study further emphasizes that explainability is not merely a technical feature but a critical factor in technology acceptance. This suggests that developers of AI-based audit tools must prioritize explainability to facilitate effective adoption by professionals. The implications are clear: audit firms should invest in AI technologies that promote transparency, while regulators must establish guidelines to govern AI use in order to maintain audit integrity. Ultimately, XAI can bridge the gap between automation and professional judgment, contributing to improved audit quality and greater trust in AI within the Indonesian auditing landscape.

5. CONCLUSION

This study concludes that Explainable Artificial Intelligence (XAI) plays a significant and positive role in enhancing the quality of auditors' decision-making in Indonesia. The findings demonstrate that key XAI features—such as transparency, interpretability, and clarity—contribute to greater confidence, accuracy, and professional judgment among auditors. The regression results further support this, showing that nearly half of the variation in decision-making quality can be explained by the presence of XAI features, highlighting its practical relevance in audit settings.

As auditing practices increasingly adopt AI-driven tools, the integration of explainable mechanisms is essential for upholding ethical standards, maintaining professional skepticism, and ensuring regulatory compliance. This study provides empirical evidence that XAI not only builds trust in technology but also empowers auditors to make sound, defensible decisions. For audit firms, the results highlight the importance of incorporating XAI into AI adoption strategies, while for policymakers, they suggest the need for regulatory frameworks that promote transparency in financial technologies. Future research is encouraged to explore additional factors such as organizational culture, regulatory pressure, or audit complexity to deepen understanding of XAI's broader impact across diverse professional environments.

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