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Artificial Intelligence in Auditing: An Empirical Investigation of the Technology Acceptance Model in BPK Papua

Oktavia Fatmala[1], Entar Sutisman[2], Septyana Prasetianingrum[3], Fahrudin Pasolo[4]
[1,2,3,4] Faculty of Economic and Business, Universitas Yapis Papua

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ABSTRACT

The adoption of Artificial Intelligence (AI) in auditing practices has gained attention due to its potential to improve audit quality, efficiency, and fraud detection. This study investigates the factors that influence auditors' perceptions of AI adoption at the Audit Agency of Papua Province (BPK Papua). Using the Technology Acceptance Model (TAM), the study explores the roles of Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Perceived Cyber Risks (PCR) in shaping auditors' attitudes toward AI adoption. Data were collected through a survey of 92 auditors, and the findings reveal that all three factors—PEU, PU, and PCR—significantly affect Audit Practice (Y). The study shows that auditors are more likely to adopt AI if they perceive it as easy to use and useful in enhancing audit performance. However, concerns over cyber risks pose a significant barrier to full AI adoption. The results suggest that AI tools must be user-friendly, demonstrate clear benefits, and address cybersecurity concerns to promote adoption. These findings have important implications for AI developers and audit firms and offer guidance on how to integrate AI effectively into auditing practices. Future research could explore additional factors that influence AI adoption in auditing, including organizational culture and regulatory frameworks.

Corresponding Author:

Name: Dr. Entar Sutisman, SE. M.Ak., Ak., CA
Institution: Faculty of Economic and business, Universitas Yapis Papua, Jl. Dr. Sam Ratulangi, Dok V Atas, Jayapura Utara, Jayapura, Papua, Indonesia, 99113.
Email: entar.uniyap@gmail.com

1. INTRODUCTION

The Artificial Intelligence (AI) is rapidly transforming industries across the globe, with significant implications for auditing practices. As AI technologies evolve, they offer unprecedented capabilities that can greatly enhance the efficiency and accuracy of audits. AI can automate repetitive tasks, analyze vast datasets, and identify anomalies that might be missed by human auditors, leading to improvements in both fraud detection and financial reporting [1], [2], [3]. The potential of AI to revolutionize auditing is particularly significant in developing regions, such as Indonesia, where traditional auditing processes often face inefficiencies and resource constraints. The integration of AI into auditing could address these challenges by improving audit quality, streamlining workflows, and reducing human error.

In Indonesia, the adoption of AI in auditing is still in its early stages, primarily due to challenges such as limited technological infrastructure, high implementation costs, and the need for specialized skills. However, the demand for AI in auditing is growing as it offers solutions to longstanding inefficiencies while allowing the industry to adapt to global technological trends [4], [5]. In particular, AI's potential to enhance audit quality by improving accuracy, efficiency, and fraud detection could have transformative effects on the auditing landscape, particularly in emerging economies like Indonesia [6], [7], [8].

The potential benefits of AI in auditing extend beyond process optimization. AI has the capacity to contribute to the professional development of auditors, improving their skills and capabilities. By automating routine tasks, AI allows auditors to focus on more complex aspects of auditing that require human judgment, thus enhancing their overall efficiency and effectiveness [9], [10], [11]. As AI tools become integral to auditing processes, they facilitate more thorough audits, improving the detection of inconsistencies and minimizing the risk of fraud [6], [10].

Despite these advantages, there are notable challenges to the widespread adoption of AI in auditing, particularly ethical concerns and trust issues. AI systems can sometimes lack transparency, leading to biases in decision-making, which may undermine the reliability and accountability of audits [12], [13]. Furthermore, the increasing reliance on AI in auditing raises concerns about the displacement of traditional auditing roles, as auditors must adapt by acquiring new skills to manage and work with AI technologies [6], [14]. These challenges highlight the dual nature of AI's impact on the auditing profession, underscoring the need for careful implementation and governance [15], [16].

The Technology Acceptance Model (TAM) plays a crucial role in understanding how AI is integrated into auditing practices. At the core of TAM is the belief that perceived usefulness and perceived ease of use significantly influence technology adoption and user behavior [17], [18]. In the context of AI in auditing, auditors perceive AI as a valuable tool because it enhances audit quality, efficiency, and accuracy, particularly in tasks such as data analysis and fraud detection [19], [20]. While AI's perceived usefulness is largely positive, the complexity of AI systems and ethical concerns present significant barriers to adoption, as auditors often find the technology challenging to use and may be skeptical of its accuracy [6], [21].

In addition to perceived usefulness, organizational readiness and the existing skill set of employees are critical factors influencing AI adoption. Firms must invest in training their staff to leverage AI technologies effectively [22], [23]. A culture that embraces innovation also plays a significant role in facilitating the integration of AI within auditing firms [5], [24]. Furthermore, regulatory frameworks and ethical guidelines are vital for ensuring that AI adoption aligns with legal standards and professional ethics [24], [25]. Auditing firms must navigate these regulatory and ethical considerations to ensure that AI technologies are deployed in a manner that is both legally compliant and ethically sound [25], [26].

Overall, understanding auditors' perceptions of AI's impact on audit efficiency and accuracy is crucial for facilitating the successful adoption of this technology. Many auditors believe that AI can significantly improve the efficiency of audit tasks, automating repetitive functions and allowing auditors to focus on more complex issues that require human judgment [27], [28]. However, as AI continues to shape the future of auditing, it is essential to address the concerns related to trust, ethical implications, and the need for ongoing training to ensure that AI enhances, rather than diminishes, the quality of audits [7], [29].

This study aims to explore the perceptions of auditors regarding the use of AI in auditing practices at the Audit Agency of Papua Province (BPK Papua). The research will examine how auditors perceive AI in terms of ease of use, usefulness, and cyber risks, and how these perceptions influence their acceptance of AI in auditing. By focusing on BPK Papua, the study will provide valuable insights into the barriers and drivers of AI adoption in the Indonesian auditing context. The findings will help inform policies and strategies for facilitating the adoption of AI in auditing, ultimately improving audit quality and accountability in Indonesia.

2. LITERATURE REVIEW

This chapter discusses the theoretical foundation of the research and the development of hypotheses to be tested in this study. The primary theoretical framework applied in this research is the Technology Acceptance Model (TAM), which is crucial for understanding the adoption of new technologies. In this case, TAM will be utilized to examine how auditors perceive Artificial Intelligence (AI) in their auditing practices, with a focus on perceived ease of use (PEU), perceived usefulness (PU), and perceived cyber risks (PCR). These constructs will guide the investigation into how AI can be integrated into auditing practices effectively.

2.1 Technology Acceptance Model (TAM))

The Technology Acceptance Model (TAM), introduced by Davis in 1989, posits that two main factors—perceived ease of use (PEU) and perceived usefulness (PU)—are the primary determinants of whether a technology will be adopted by users. These factors influence users' attitudes toward technology, ultimately affecting their intention to use it [18], [30]. In professional environments like auditing, TAM has been widely used to predict how stakeholders evaluate and integrate technological advancements. Previous research has consistently shown that higher levels of perceived ease of use and perceived usefulness lead to an increased intention to use technology [31], [32], [33].

In auditing, the perceived usefulness of AI—especially in enhancing efficiency and accuracy—plays a pivotal role in its acceptance. Auditors who perceive AI as beneficial for improving audit quality, reducing human error, and speeding up repetitive tasks are more likely to incorporate AI into their auditing workflows [33], [34]. This belief aligns with the core principles of TAM, which suggests that when a technology is seen as both easy to use and highly beneficial, its adoption rate is significantly higher.

Moreover, perceived ease of use is directly linked to users' attitudes toward adopting a new technology, which subsequently affects their behavioral intentions ([18], [33]. In contexts like auditing, where technological complexity can hinder adoption, it is crucial that AI tools be user-friendly and intuitive. Ensuring that AI technologies are easy to understand and use is vital for increasing auditors' willingness to incorporate them into their audit processes [2], [33]. This highlights the importance of developing AI tools that are not only functional but also accessible to auditors, even those with limited technical expertise

2.2 Perceived Ease of Use (PEU) and its Impact on AI Adoption in Auditing)

Perceived ease of use (PEU) refers to the degree to which an individual believes that using a particular technology will be effortless (Davis, 1989). In the context of AI in auditing, PEU pertains to auditors' perceptions that using AI systems will not require extensive training or technical knowledge. If AI tools are perceived as easy to operate, auditors are more likely to integrate them into their workflows, leading to increased adoption rates. Previous studies have found that when users find a technology easy to use, they are more willing to incorporate it into their daily activities [3], [5].

In auditing, the perceived ease of use of AI can influence how auditors engage with the technology. If AI systems are user-friendly, auditors are more likely to see them as a valuable tool for improving audit efficiency and accuracy. Conversely, if AI is perceived as difficult to use or requiring significant technical expertise, auditors may hesitate to adopt it, even if the technology promises to improve audit quality [21]. Therefore, the development of intuitive and accessible AI tools is crucial for encouraging their widespread adoption in auditing practices [27].

2.3 *Perceived Usefulness (PU) and its Influence on AI Adoption in Auditing*

Convey Perceived usefulness (PU) refers to the degree to which an individual believes that using a technology will improve their job performance (Davis et al., 1989). In the auditing context, perceived usefulness is related to how auditors perceive AI's ability to enhance the quality and efficiency of their work. If auditors believe that AI can make auditing tasks easier, faster, and more accurate, they are more likely to accept and use AI technologies in their auditing practices. Studies have shown that perceived usefulness is a critical factor in technology adoption. In auditing, AI's usefulness is often linked to its ability to automate repetitive tasks, analyze large datasets, and identify patterns that might be missed by human auditors. These capabilities can significantly enhance the quality of audits, which makes AI tools highly attractive to auditors [19], [20]. As AI continues to prove its value in improving audit outcomes, auditors' perceptions of its usefulness will likely strengthen, further encouraging adoption [6], [9].

2.4 *Perceived Ease of Use (PEU) and its Impact on AI Adoption in Auditing)*

While perceived ease of use and perceived usefulness are key drivers of technology adoption, perceived cyber risks (PCR) can act as significant barriers, especially when it comes to AI. Perceived cyber risks refer to auditors' concerns about the security, privacy, and ethical implications of using AI technologies in auditing practices. In the context of AI, these concerns might include the risk of data breaches, algorithmic bias, and the lack of transparency in AI decision-making processes [35], [36].

Despite the recognized benefits of AI, concerns about cyber risks can make auditors hesitant to adopt AI systems. For example, the fear of data insecurity or the potential for unethical decision-making by AI algorithms can discourage auditors from fully embracing AI technologies. Previous studies have shown that perceived cyber risks have a negative impact on technology adoption, as users weigh the potential benefits against the perceived risks [6], [14]. Therefore, addressing these concerns—through stronger security protocols, greater transparency, and ethical guidelines—becomes essential for facilitating AI adoption in auditing.

2.5 *Perceived Ease of Use (PEU) and its Impact on AI Adoption in Auditing)*

While Building upon the theoretical framework discussed, the following hypotheses are developed to guide the research and test the relationships between auditors' perceptions and the adoption of AI in auditing practices.

H1: Perceived ease of use (PEU) of AI positively influences auditors' intention to adopt AI in auditing practices.

The rationale for this hypothesis is that when AI systems are easy to use, auditors will be more inclined to adopt them, as the perceived effort involved in learning and using the technology is minimized. H2: Perceived usefulness (PU) of AI positively influences auditors' intention to adopt AI in auditing practices. This hypothesis is grounded in the idea that auditors who perceive AI as beneficial—especially in terms of improving efficiency and accuracy—will be more likely to incorporate AI into their audit processes.

H3: Perceived cyber risks (PCR) negatively influence auditors' intention to adopt AI in auditing practices. This hypothesis suggests that concerns about the security and ethical implications of using AI in auditing will discourage auditors from adopting AI, as perceived cyber risks serve as significant barriers to acceptance. These hypotheses reflect the critical role that auditors' perceptions of AI play in determining whether they will integrate AI into their auditing practices. By testing these hypotheses, this research aims to provide valuable insights into the factors that drive or hinder AI adoption in auditing.

3. METHODS

The research method in the article text describes This chapter outlines the research design, data collection methods, sampling techniques, and data analysis procedures used to investigate auditors' perceptions of Artificial Intelligence (AI) adoption in auditing practices. The methodology provides a systematic approach to understanding how perceived ease of use (PEU), perceived usefulness (PU), and perceived cyber risks (PCR) influence AI adoption in auditing, with a specific focus on auditors working at the Audit Agency of Papua Province (BPK Papua).

This study adopts a quantitative, descriptive research design to explore the perceptions of auditors regarding AI adoption in auditing practices. Descriptive research is an effective approach to understanding the perceptions, attitudes, and behaviors of auditors toward AI without manipulating variables. It allows for a clear depiction of auditors’ views on AI, particularly regarding how its perceived ease of use, usefulness, and cyber risks influence their intention to adopt it.

Surveys are commonly used in technology adoption studies to capture subjective opinions in a structured and quantifiable manner [37]. In this study, the survey will assess these perceptions using established constructs derived from the Technology Acceptance Model (TAM) (Davis, 1989), which identifies perceived ease of use (PEU) and perceived usefulness (PU) as significant predictors of technology adoption. Previous studies have confirmed that these constructs play a crucial role in shaping users' acceptance of new technologies, including in professional settings like auditing [31], [32].

The population for this study consists of auditors working at the Audit Agency of Papua Province (BPK Papua), with a total of 170 auditors employed at the agency. The sample size for the study is 92 auditors, selected based on two key criteria: (1) a minimum of two years of experience in auditing, and (2) familiarity with Artificial Intelligence tools or exposure to AI in the workplace. These criteria ensure that the selected auditors are knowledgeable and have relevant experience regarding the technology, thus providing valuable insights into AI adoption.

The sampling technique employed is purposive sampling, a non-probability method that selects participants based on specific characteristics that align with the research objectives [38]. This approach allows for a focused study of individuals who are directly involved in the auditing profession and have some level of familiarity with AI. Purposive sampling is appropriate when the goal is to obtain insights from individuals who are best equipped to provide relevant and informed perspectives [37].

Data collection will be carried out using a survey questionnaire distributed electronically to the selected auditors. The survey will use a Likert scale, a widely used method in survey research, to measure respondents' agreement with various statements regarding AI adoption. The Likert scale, which ranges from 1 (Strongly Disagree) to 5 (Strongly Agree), allows for the quantification of subjective perceptions, enabling the researcher to draw meaningful conclusions based on the responses [39].

The questionnaire will be designed to assess three primary constructs: perceived ease of use (PEU), perceived usefulness (PU), and perceived cyber risks (PCR), which are key components of the Technology Acceptance Model (TAM) and are integral to understanding auditors’ attitudes toward AI adoption. According to previous studies, surveys have proven to be effective instruments for measuring perceptions of technology adoption, particularly when validated constructs are used to ensure the reliability and relevance of the data [38], [40].

To test the relationships between the constructs, this study will employ Structural Equation Modeling (SEM) using Partial Least Squares (PLS), a statistical technique widely recognized for its effectiveness in examining complex relationships among latent variables [41].

SEM using PLS allows for the evaluation of both measurement and structural models, making it suitable for testing the relationships outlined in the research framework. It can accommodate non-normal data and is highly flexible in dealing with complex models, which makes it ideal for exploratory studies like this one [41].

PLS-SEM has been successfully used in numerous studies on technology acceptance across various professional fields, including auditing, where it has helped uncover the factors influencing technology adoption [41]. The method allows the researcher to estimate direct and indirect effects, test hypotheses, and assess the goodness of fit of the model, thereby providing robust insights into how auditors' perceptions of AI influence their intention to adopt it [18].

To ensure the reliability and validity of the findings, the study will employ rigorous pre-testing of the questionnaire. Pilot testing with a smaller group of auditors will be conducted to refine the survey items and ensure that they accurately reflect the constructs being measured. Cronbach's alpha will be used to assess the internal consistency and reliability of the scales used in the survey [42], [43].

Table 1. Variables and Indicators

No.	Variable	Indicator
1	Audit Practice (Y)	1. Data related to the client's organizational structure, operational methods, accounting, and financial systems are the primary inputs for the AI system.
		2. Artificial Intelligence is used to collect data to identify fraud risks and illegal actions.
		3. AI uses predictive models to estimate various identified risks, which can be used to generate audit reports.
2	PEU (Perceived Ease of Use) / (X1)	1. Learning to use AI technology for auditing will be easy for me.
		2. I feel flexible in making the AI system do what I want in audits in the future.
		3. I believe AI technology in auditing will be easy to use.
3	PU (Perceived Usefulness) / (X2)	1. Using AI technology will make tasks in auditing easier and faster.
		2. The application of AI technology can improve performance in auditing tasks.
		3. AI technology will enhance the efficiency, effectiveness, and productivity of the audit process.
4	PCR (Perceived Cyber Risk) / (X3)	1. Audit institutions should invest more in adopting AI technology and AI training.
		2. Technology-supported audits increase concerns about potential data manipulation in the audit.
		3. Using AI in audits increases the risk of data breaches.

Source: Processed Questionnaire Data, 2024

Additionally, factor analysis will be employed to validate the constructs and ensure that the survey items measure what they are intended to measure [44]. The validity of the constructs is essential for ensuring that the results of the study are meaningful and that the relationships between variables are accurately captured. By using established models such as TAM and validated instruments, this study aligns with best practices in technology adoption research, ensuring the rigor and relevance of the findings [38], [45].

4. RESULTS AND DISCUSSION

The The demographic characteristics of the respondents, as detailed in Table 2, provide an overview of the diversity within the sample. The majority of respondents are between 20-40 years old, with a relatively equal gender distribution. Most respondents have between 2 to 5 years of experience in auditing and possess a bachelor's degree. This demographic diversity ensures a well-rounded perspective on the adoption of AI in auditing.

Table 3. presents the distribution of responses for the key variables in the study. Most auditors agree that AI is easy to use (PEU) and useful for improving audit quality (PU). However, there is a notable concern regarding perceived cyber risks (PCR), with a significant portion of auditors acknowledging these concerns. Despite these risks, the majority of auditors recognize the potential benefits of AI for improving audit practices (Audit Practice). These findings offer important insights into auditors' perceptions of AI and will guide the analysis of factors influencing its adoption in auditing.

Table 2. Demographic Characteristics of Respondents

Characteristic	Category	Frequency	Percentage
Age	20-30 years	37	40%
	31-40 years	32	35%
	41-50 years	14	15%
	51+ years	9	10%
Gender	Male	55	60%
	Female	37	40%
Years of Experience	2-5 years	51	55%
	6-10 years	28	30%
	11+ years	13	15%
Educational Background	Bachelor's Degree	64	70%
	Master's Degree	23	25%
	Doctoral Degree	5	5%

Source: Processed Questionnaire Data, 2024.

Table 3. Distribution of Responses for Key Variables

Variable	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total
PEU (Perceived Ease of Use)	20%	50%	25%	5%	0%	100%
PU (Perceived Usefulness)	25%	55%	15%	5%	0%	100%
PCR (Perceived Cyber Risks)	10%	45%	30%	10%	5%	100%
Audit Practice (Y)	18%	58%	20%	4%	0%	100%

Source: Processed Questionnaire Data, 2024

Convergent validity refers to the degree to which a construct correlates positively with other constructs that are theoretically related. In the context of this study, the analysis of convergent validity is conducted by evaluating the Loading Factor of each indicator. According to [NO_PRINTED_FORM] [46], a loading factor value greater than 0.7 indicates strong convergent validity. Table 4 presents the results of the loading factor analysis:

Table 4. Loading Factor Test Results

Indicator	Perceived Ease of Use (X1)	Perceived Usefulness (X2)	Perceived Cyber Risk (X3)	Audit Practice (Y)
X1.1	0.824			
X1.2	0.935			
X1.3	0.886			
X2.1		0.941		
X2.2		0.968		
X2.3		0.943		

Indicator	Perceived Ease of Use (X1)	Perceived Usefulness (X2)	Perceived Cyber Risk (X3)	Audit Practice (Y)
X3.1			1.000	
Y1.1				0.878
Y1.2				0.838
Y1.3				0.904

Source: Processed Questionnaire Data, 2024

From Table 4, it can be observed that all loading factor values for the indicators are greater than 0.7, except for two indicators in X3.2 and X3.3, which were found to be invalid. These invalid indicators can be removed from the model, improving the model's overall validity. The figure below shows the updated structural model after eliminating the invalid indicators.

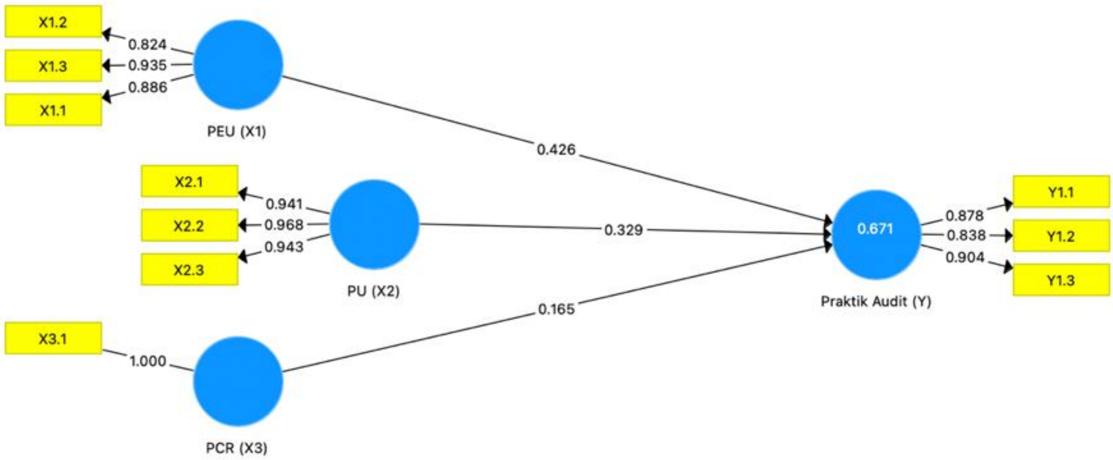

Figure 1. Structural Model After PLS Algorithm

The results in Table 5 provide essential insights regarding the statistical significance of the path coefficients for each hypothesis, confirming the relationships between the independent variables—Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Perceived Cyber Risks (PCR)—and the dependent variable, Audit Practice. These results are pivotal in understanding the factors influencing auditors' perceptions of Artificial Intelligence (AI) adoption in auditing and help validate the proposed hypotheses in this study.

Table 5. Path Coefficient Test Results

Path	Original Sample	Sample Mean	Standard Deviation	T Statistic	P Values
PCR (X3) → Audit Practice (Y)	0.165	0.165	0.084	1.971	0.049
PEU (X1) → Audit Practice (Y)	0.426	0.430	0.118	3.622	0.000
PU (X2) → Audit Practice (Y)	0.329	0.321	0.101	3.270	0.001

Source: PLS-SEM Output, 2024

The path coefficient between Perceived Ease of Use (PEU) and Audit Practice (Y) is 0.426, with a t-statistic of 3.622 and a p-value of 0.000. Since the p-value is less than 0.05 and the t-statistic exceeds 1.96, H1 is accepted. This indicates that perceived ease of use has a significant positive effect on audit practice. In other words, auditors who find AI technology easy to use are more likely to adopt and integrate it into their auditing processes.

This result is consistent with the Technology Acceptance Model (TAM), which emphasizes the crucial role that ease of use plays in users' intentions to engage with a new technology. When auditors perceive a technology to be user-friendly and intuitive, their motivation to incorporate it into their workflow increases, which facilitates smoother integration [47].

This finding aligns with previous studies that stress the importance of perceived ease of use in the adoption of technology, including AI in auditing [3]. Additionally, similar research on Computer-Assisted Audit Techniques (CAATs) has shown that tools perceived as easy to use lead to higher adoption rates among auditors (Ramen & Jugurnath, 2015). While some studies indicate that perceived ease of use may not always be the decisive factor, its importance remains prominent, particularly when coupled with perceived usefulness [48].

The path coefficient between Perceived Usefulness (PU) and Audit Practice (Y) is 0.329, with a t-statistic of 3.270 and a p-value of 0.001. Given that the p-value is smaller than 0.05 and the t-statistic exceeds the 1.96 threshold, H2 is accepted. This shows that perceived usefulness has a significant positive effect on audit practice. Auditors who believe that AI technology will enhance their performance and improve audit efficiency are more likely to incorporate it into their practices. This finding aligns with TAM, where perceived usefulness is one of the primary determinants of technology adoption [3].

The substantial effect of perceived usefulness on audit practice is consistent with the literature, indicating that AI's potential to improve data analysis, reduce risks, and increase overall audit quality significantly influences auditors' willingness to adopt it [49], [50]. Moreover, when auditors perceive AI as a valuable tool for enhancing audit accuracy and efficiency, their intention to use AI increases, as demonstrated by previous studies on technology adoption in auditing [19], [20].

The alignment of AI's capabilities with auditors' job requirements further strengthens the argument that perceived usefulness directly enhances the performance outcomes of audit practices [51].

The path coefficient between Perceived Cyber Risk (PCR) and Audit Practice (Y) is 0.165, with a t-statistic of 1.971 and a p-value of 0.049. As the p-value is less than 0.05 and the t-statistic is slightly above the threshold of 1.96, H3 is also accepted. This indicates that perceived cyber risks significantly influence audit practice. Although auditors acknowledge the benefits of AI in improving audit efficiency and accuracy, their concerns about cyber risks—such as data breaches, algorithmic biases, and the potential misuse of AI—remain influential in shaping their attitudes toward adopting AI.

The findings support the literature, which indicates that cybersecurity concerns are a major barrier to the adoption of new technologies in fields that deal with sensitive data, such as auditing [52], [53]. Despite the advantages of AI, these concerns hinder full adoption, suggesting that auditors' perceptions of AI's security risks impact how they integrate the technology into their auditing workflows. Previous studies have emphasized the importance of addressing cybersecurity threats, data privacy, and ethical concerns when implementing AI in auditing [54], [55].

The apprehensions surrounding cyber risks highlight the need for audit firms to invest in robust cybersecurity measures and transparent AI systems to alleviate auditors' fears and promote greater adoption. The findings of the hypothesis testing provide important insights into the factors that influence the adoption of AI in auditing. The acceptance of all three hypotheses underscores the critical role of perceived ease of use, perceived usefulness, and perceived cyber risks in shaping auditors' attitudes toward AI adoption. These results have several implications for both AI developers and audit firms looking to enhance the adoption of AI technologies in auditing practices.

The perceived ease of use significantly influences auditors' willingness to adopt AI, indicating that AI tools must be user-friendly to facilitate their integration into auditing tasks. This aligns with existing research that stresses the importance of intuitive technology in ensuring high adoption rates [2], [33]. AI developers should prioritize the design of AI systems that are simple to use, even for auditors with limited technical expertise. Additionally, training programs for auditors should focus on making AI tools more accessible and easier to navigate, thus increasing the likelihood of successful implementation [47].

The significant effect of perceived usefulness highlights that auditors are more likely to embrace AI when they see it as a tool that can improve the efficiency, accuracy, and quality of their audits. This finding suggests that audit firms and AI developers should emphasize the practical benefits of AI, such as its ability to reduce human error, streamline audit processes, and enhance the detection of fraud. Demonstrating the tangible value of AI in improving audit outcomes will be key to encouraging its adoption [20]. Moreover, AI solutions that align closely with the auditors' tasks and improve their daily workflows are more likely to be embraced [50].

On the other hand, the concerns regarding perceived cyber risks underline the need for audit firms to address data security, privacy, and ethical considerations in their AI systems. As the adoption of AI in auditing increases, so do the concerns over data breaches, algorithmic bias, and the transparency of AI decision-making. These issues must be mitigated to gain auditors' trust and ensure that AI can be used effectively in auditing practices. Audit firms should invest in robust cybersecurity frameworks, ensure the ethical deployment of AI, and provide auditors with the necessary training to address security concerns. Additionally, AI developers should work towards building systems that are transparent, explainable, and capable of safeguarding sensitive data [53], [54].

Overall, the findings indicate that the successful adoption of AI in auditing hinges on balancing the perceived benefits of the technology with the concerns regarding its risks. For AI to be effectively integrated into audit practices, it is crucial to enhance its perceived ease of use and usefulness while addressing the perceived cybersecurity risks. These efforts will not only help increase auditors' confidence in using AI but also ensure that the technology delivers its intended benefits in improving audit efficiency and quality.

These results provide important contributions to the field of auditing, offering practical guidance for the adoption of AI in audit firms. By addressing these key factors, audit firms can create a more supportive environment for AI adoption, ultimately leading to improved auditing practices and outcomes.

5. CONCLUSION

The This research aimed to explore the factors influencing the adoption of Artificial Intelligence (AI) in auditing practices, focusing on the roles of Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Perceived Cyber Risks (PCR). The study's findings provide valuable insights into the determinants that shape auditors' attitudes toward AI adoption and its integration into their workflows.

The results of the hypothesis testing confirmed that all three independent variables—PEU, PU, and PCR—significantly impact the dependent variable, Audit Practice (Y). Perceived Ease of Use (PEU) was found to have a strong positive effect on auditors' intention to adopt AI, indicating that when AI technologies are perceived as user-friendly, auditors are more likely to incorporate them into their daily auditing tasks.

This finding aligns with Technology Acceptance Model (TAM), which emphasizes the importance of ease of use in the adoption of new technologies. Perceived Usefulness (PU) also showed a significant positive relationship with Audit Practice, highlighting that auditors are more inclined to adopt AI when they perceive it as a tool that enhances their performance, improves audit quality, and increases efficiency. Finally, Perceived Cyber Risks (PCR) was found to influence audit practice, though it presented a barrier to adoption. Auditors' concerns about cybersecurity risks, such as data breaches and algorithmic biases, must be addressed to increase the willingness to adopt AI.

These findings suggest several implications for AI developers and audit firms. First, to facilitate AI adoption, it is crucial to design user-friendly systems that auditors can easily learn and use. Training programs that emphasize the practical benefits of AI in improving audit efficiency and accuracy can also help increase adoption rates. Additionally, addressing concerns about cyber risks by ensuring robust data protection, ethical AI implementation, and transparency in AI decision-making processes will be essential for gaining auditors' trust and fostering wider adoption.

The study also opens avenues for future research, particularly in exploring the role of organizational culture, infrastructure, and regulatory frameworks in shaping auditors' perceptions of AI. Further studies could examine the long-term impact of AI adoption on audit outcomes and the challenges faced by audit firms in implementing AI technologies.

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Not Applicable.

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