# Decoding AI Adoption: Unveiling the Drivers behind Internal Auditors' Integration of AI in Auditing Operations

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*Abstract:* - Finding the elements that motivate auditors to use artificial intelligence in internal auditing procedures is the main goal of this study. This study investigates how people and technology interact from the viewpoint of individual workers. 160 valid responses were gathered from internal auditing staff members working for various companies in Greater Jakarta, Indonesia (Jakarta, Bogor, Depok, Tangerang, and Bekasi) where purposive sampling and a quantitative research method were used. The Technology Acceptance Model (TAM) served as the theoretical basis for the construction of the structural model, and the data was analyzed using partial least squares structural equation modelling (PLS-SEM). The result of this study determines that intention to use AI in internal auditing by auditors' is highly correlated with perceived ease of use, perceived usefulness, and sense of trust. This study also discovers that intention to use AI in internal auditing is significantly affected by attitude, awareness, and innovativeness. These results implicate that significant practical implications and might be useful to internal auditors, audit firms, companies, technology providers, investors, shareholders and professional associations.

*Key-Words:* - Artificial Intelligence, Auditing, Attitude, Adoption Intention, Perceived Usefulness, Innovativeness, Awareness.

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## 1 Introduction

The emergence of disruptive information and communication technologies (ICTs) has led professionals and organizations to reevaluate their operational structures in recent years, [1], [2], [3]. According to [4], AI is expected to contribute up to 14% to the global GDP by 2030, equivalent to $15.7 trillion, [5]. This contribution could be driven by greater output, fewer faults, increased efficiency, and more product customization. Additionally, as corporate processes get more complex, technology-driven decision-making tools are becoming more and more required, which is drastically altering accounting and auditing procedures, [6], [7], [8], [9]. To maintain a good reputation, companies are using advanced technology to ensure reliable and efficient internal audits, [10], [11]. Auditing has always been a labour-intensive profession that demands a high degree of efficiency and competitiveness, particularly to boost the output of junior auditors, [12], [13]. The application of developing technology in auditing has led to significant breakthroughs, including greater data protection for confidential internal data, faster stakeholder communication, more efficient audit

evidence collecting, and increased productivity, [12], [14].

According to [15], for example, AI investments greatly improve audit quality, reduce costs, and progressively reduce audit staffing levels. Over the course of three years, the likelihood of restatements decreased by 5%, audit fees decreased by 0.9%, and the number of accounting staff decreased by 3.6%, reaching 7.1% by the fourth year. Additionally, for every standard deviation increase in AI investment, restatements fell by 2.9% between 2010 and 2013 and by 4.9% between 2014 and 2017. The effectiveness and efficiency of statutory audits have been greatly enhanced by these advancements. [16] posited that 97% of auditors globally acknowledge the advantages and effectiveness of AI in auditing. As a result, robotic process automation and artificial intelligence (AI) have the potential to change auditing and accounting procedures, [17], [18]. AI is now essential for auditors, having progressed from basic software to sophisticated systems driven by sophisticated algorithms, [19]. Using AI in auditing has been studied previously, [15], [20] and AI is essential for maintaining competitiveness because of its advantages, which include increased reliability, productivity, and cost-effectiveness. As a result, auditors are increasingly utilizing AI technology to keep ahead of the competition, even if the number of human auditor roles may decrease as the sector grows.

Although expenditures in AI have increased recently in a number of industries, there is still conflicting data regarding how AI affects business productivity, [21]. The lack of firm-level data to effectively quantify AI adoption is a major barrier, [22], [23]. Furthermore, the effects of AI differ for different professions, with some being more vulnerable to AI algorithms' replacement or enhancement which caused, limited influence in some industries and concentrated effects in others, [24]. Artificial intelligence (AI) aims to increase audit quality by improving risk assessment, fraud detection, and auditor focus on high-risk areas, [25]. For instance, through real-time transaction analysis, [26] found that AI investments in auditing can improve accuracy by 50%, reduced audit risks by up to 30%, and shorten audit cycle times by 40%. These advancements enhance productivity while minimizing human error. One of the primary challenges that many auditors have when deploying AI is the decreased explainability of large AI models, which often become opaque "black boxes" as their predictive performance increases, [27], [28]. Despite these challenges, data input and accounting record analysis are just two of the operations that artificial intelligence (AI) is automating to transform auditing. AI is capable of reviewing all data, writing scripts, conducting audit tests, and identifying fraudulent entries, in contrast to human auditors, [26], [29]. This lowers human mistake while greatly increasing audit accuracy, cost-effectiveness, and efficiency.

However, many students are unprepared for these changing industry expectations because accounting education does not provide AI training, [30], [31]. High implementation costs, the requirement for talent development, and controlling bias and data quality are further obstacles in integrating AI, [25]. Addressing these issues is crucial to maximizing AI's potential as auditors work to deliver cutting-edge services, [32], [33].

Prior research has looked into auditors' plans to utilize AI from a number of angles. For example, [17] investigated how AI affects auditor behavior during auditing procedures, whereas [12] investigated the ethical concerns surrounding AI in auditing. [19] looked into how Industry 4.0 and AI can affect accounting and auditing. Other studies have examined the potential of AI to co-piloted auditing [20], enhance digital transformation [25], and audit processes [28]. The majority of these studies, however, are exploratory in nature and did not examine the primary determinants of auditors' decisions to use AI in internal auditing. [26] highlighted that auditors' attitudes, shaped by perceived usefulness and ease of use, significantly influence their adoption decisions. Similarly, [34] found that finance and accounting leaders tend to adopt AI when they have positive attitudes and awareness of technology. [35] demonstrated that trust in AI-supported technology strongly shapes users' positive attitudes toward its use. Furthermore, creative auditors are more likely to adopt digital technology, according to [36]. Despite these revelations, prior research has seldom examined the factors impacting internal auditors' intents to employ AI in internal auditing operations, particularly from the viewpoint of developing nations like Indonesia. In order to forecast AI adoption intentions in internal auditing, especially in Indonesia, it is imperative to comprehend these behavioral characteristics. In order to fill these gaps, our study seeks to respond to the following important questions:

Q1: To what extent do perceive usefulness, perceived ease of use, and a sense of trust influence internal auditors' positive attitudes toward AI in auditing?

Q2: To what extent do attitude, awareness, and innovativeness impact internal auditors' intention to use AI in auditing operations?

Thus, in an era where technology is revolutionizing companies, this study investigated the critical factors influencing AI adoption decisions in internal audit operations. In an attempt to give businesses, technology suppliers, shareholders, internal auditors, audit firms, investors, and professional associations relevant information, the study examined these significant subjects. When integrating artificial intelligence (AI) into their audit processes, the findings are well-positioned to address the most pressing problems that auditors face. Theoretically, this study is to understand of AI adoption behavior among internal auditors by extending the Technology Acceptance Model (ETAM). In a variety of geographical situations, the Extended Technology Acceptance Model (ETAM) has been extensively used to investigate auditors' intents to use AI-supported technologies for auditing activities. For example, [37] examined the transformative impact of AI and Industry 4.0 on Saudi Arabia's auditing and accounting practices utilizing ETAM as their paradigm. In a similar vein, [38] investigated the factors influencing Egypt's adoption of auditing data analytics technology using ETAM. In addition to these studies, [38] focused on the implementation of computer-assisted auditing technology, while [39] investigated the incorporation of AI in Vietnam's accounting and auditing. Using the TAM framework, [40] investigated the impact of technology readiness in AI adoption for accounting operations in the United States. Despite these excellent contributions, there is still a big gap because none of the research have extended TAM to incorporate Sense of Trust, Awareness, or Innovativeness in their theoretical frameworks. This is especially true when taking into account the goal of implementing AI in internal auditing. This current study filled this gap and contributed a new viewpoint to the expanding body of research on the use of AI in auditing procedures by incorporating these characteristics. This study employed PLS-SEM, a dependable regression technique that is well-known for its ability to assess complex structural models and for being suitable for exploratory research, especially when working with smaller sample sizes and novel or immature hypotheses, [41]. Ultimately, this study adds both theoretical and practical insights to the literature on AI-based internal auditing, paving the way for higher stakeholder trust in internal audit reports and improved audit operations accuracy.

This study was structured into several sections. In Section 2, the theoretical framework was introduced, the current literature on the adoption of internal auditing was thoroughly reviewed, and the hypotheses were formulated. Section 3, the research methodology and the data gathering procedure was discussed and continued by data analysis methods and the findings in Section 4. Section 5 analyzed the results and contrasted them with previous research. The study's theoretical and management ramifications were examined in Section 6. The research's conclusions, limitations, and future research are discussed in Section 7 and 8.

# 2 Literature Review

## 2.1 Theoretical Background and Hypothesis Development

The Technology Acceptance Model (TAM) was first presented in 1986, [42]. Perceived usefulness (PU) is the idea that technology enhances performance, and perceived ease of use (PEOU) are highlighted as the two main elements driving adoption, [42], [43]. [44] stated that PEOU and PU influence users' attitudes and behavioral intentions, which affects their actual usage. TAM provides insights into creating user-friendly technology to increase adoption and is frequently used in fields like business, education, and healthcare.

However, TAM has some limitations, such as its emphasis on personal characteristics at the expense of more extensive organizational, cultural, and social influences on the adoption of technology, [19]. It ignores emotional or psychological factors in favor of assuming a logical decision-making process. Additionally, TAM is less useful in explaining complex post-adoption behaviors. Furthermore, in many circumstances, its simplicity may not fully capture the intricate dynamics of technology adoption, even with its benefits. To get over these issues and increase TAM's forecast accuracy, researchers have proposed enlarging the model by including relevant variables specific to the technology under study, [19], [28]. This recommendation states that in order to more fully investigate internal auditors' intents to use AI technology, the current study extends TAM by adding variables such as awareness [45], trust [46], and innovativeness [45] (Figure 1).

The effect of AI on auditing has been the subject of numerous studies from various angles, [19], [47]. [40] claims that perceived utility (PU) and ease of use (PEOU) have a significant

mediating effect on the relationship between the intention to employ AI in accounting and auditing, as well as technology readiness.

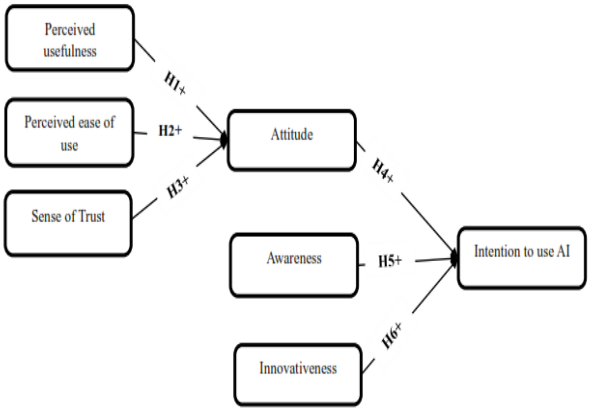


Fig. 1: Theoretical framework

According to [40], several elements including perceived utility and ease of use (PEOU), organizational and societal impacts, facilitating conditions, trust, and satisfaction are influencing the auditors' adoption behaviour of AI-assisted audit methods. [34] state that the main factors influencing accounting professionals' usage of AI in auditing procedures are usability and technological constraints. In the same way, [34] discovered that performance expectations, attitude, skill, and technical capabilities had a significant impact on the intentions of heads of finance and accounting departments to use AI. [48] emphasised the significance of performance expectations and social influence in motivating auditors to use cutting-edge technology in auditing. There is a clear research deficit in developing yet technologically advanced nations like Indonesia, despite the fact that these prior studies have mostly concentrated on AI adoption in more developed nations like the USA, Italy, China, the United Arab Emirates, Malaysia, and Saudi Arabia. In today's competitive business market, conducting cost-effective, high-quality audits requires an understanding of the factors driving the use of AI in internal auditing. Table 1 (Appendix) is given an overview of previous studies that are relevant to this inquiry.

## 2.2 AI for Internal Audit

The application of AI in internal auditing is a revolutionary shift in auditing practices since it increases accuracy, efficiency, and risk management, [49], [50]. AI enhances the quality of auditing by utilizing automation, analysing large datasets and distinguish the irregularities that auditors fail to notice, [15]. With the help of AI technology, auditors can concentrate on more strategic, value-added tasks, like employing predictive analytics to foresee and reduce possible risks and real-time financial transaction monitoring to guarantee continuous regulatory compliance, [51], [52]. Furthermore, audit processes are continuously being improved by AI's machine learning capabilities, [51].

Nevertheless, there are also some disadvantages to using AI in auditing, including the need for auditors to improve their skills, adapt to new methods, and deal with ethical conundrums such data protection, [49], [53], [54].

## 2.3 Perceived Usefulness (PU) and Attitude

Whether or if a new IT system is believed to enhance job performance is crucial to its perceived usefulness, [19]. This concept is especially crucial when it comes to AI in internal auditing because auditors' perceptions of its usefulness have a big impact on their attitudes towards adoption, [54], [55]. As auditors see the tangible benefits of AI, such higher efficiency, unparalleled accuracy, and the ability to handle massive datasets, their opinions regarding the technology improve, [15], [53]. This change occurs as they realise how AI may reduce human mistake, streamline monotonous tasks, and generate more profound and perceptive insights [45].

When these advantages become evident, initial scepticism usually gives way to acceptance and even excitement [56], [57]. In order to focus on strategic, judgment-based work that genuinely provides value, auditors begin to see that AI serve as a complement tool to their expertise rather than a replacement, [33]. This optimistic outlook, meanwhile, depends on how beneficial people believe AI will be for their daily tasks, [58]. Opposition, however, may endure if AI is perceived as being unduly complicated or threatening job security. According to [19] and [59], promoting a favourable attitude towards AI's incorporation inside internal auditing requires proving the technology's worth. Therefore, the following hypothesis is formulated:

*H1: Perceived usefulness has a significant influence on Attitude.*

## 2.4 Perceived Ease of Use (PEOU) and Attitude

Perceived ease of use is a person's estimate of the amount of work needed to adapt a new work pattern, [60], [61]. The attitudes of auditors on AI-assisted internal auditing are significantly influenced by

PEOU, [15]. When auditors perceive AI systems as intuitive and user-friendly, they are more likely to have a positive assessment of them. A more smooth and appealing transition is made possible by the ease with which AI may be incorporated into regular auditing tasks, requiring less effort and a lower learning curve. According to [46] and [62], a well-designed AI system simplifies complex auditing procedures and facilitates auditors' learning and usage of the technology.

This ease of contact fosters a sense of competence and confidence in the auditors, improving their overall experience and satisfaction with the AI tools, [63]. As auditors become more accustomed to AI, their initial reluctance usually gives way to enthusiasm and acceptance. Easy-to-use AI systems are also seen by auditors as a useful tool rather than a hindrance, which allays concerns about job disruption or increased workload, [64]. This positive view promotes increased involvement and use of AI technologies. AI-supported auditing solutions must be easy to use in order to encourage a positive attitude among auditors and enable their successful integration into internal auditing procedures. According to [15], PEOU contributes to the positive attitudes on the use of AI in external auditing. As a result, the following hypothesis is formulated:

*H2: Perceived ease of use has a significant influence on attitude.*

## 2.5 Sense of Trust and Attitude

The degree of trust auditors has in the technology has a significant impact on how they feel about the use of AI-supported internal auditing, [54]. [12] claimed that auditors who trust AI to safeguard sensitive data and offer reliable insights view it as a powerful tool that enhances their work. This trust changes their mindset, which encourages more zeal, acceptance, and proactive use of AI. It reassures auditors that AI may augment their expertise without compromising integrity or posing unnecessary risks, [65].

However, if concerns are expressed about the reliability, data security, or ethical standards of AI, auditors may become hesitant or sceptical, [54]. Building and maintaining sense of trust in AI is necessary to promote positive attitudes among auditors. With its ability to increase efficiency, accuracy, and judgement, this confidence ensures that AI will be successfully integrated into internal audits. In their study, [10] discovered a link between trust and attitudes towards the use of AI. Therefore, the following hypothesis may be proposed for this research:

*H3: Sense of Trust has a significant influence on Attitude.*

## 2.6 Attitude and Intention to Use AI

Attitude is a term that describes a person's favourable or negative evaluation, sentiment, or opinion towards a particular thing, person, idea, or situation, [36]. AI is seen as a helpful tool that enhances efficiency, accuracy, and decision-making—has a significant impact on their intention to use AI, [15], [66]. AI has a potential to simplify complex tasks, lower errors, and produce insightful information which in turn will boost confidence in its implementation, [9]. In addition to fostering auditors' acceptance of AI, a positive attitude motivates them to engage with and adapt to emerging technological paradigms, [17].

A successful AI integration requires this proactive strategy, since it encourages deeper participation and continuous research into the benefits of AI. However, a skewed attitude toward AI as complex, unreliable, or a threat to professional occupations could significantly hinder adoption, [36]. According to [15], enhancing auditors' desire to integrate AI into internal auditing practices necessitates cultivating a positive mindset through targeted education, highlighting AI's potential, and allaying anxieties. As a result, the following hypothesis might be proposed for this study:

*H4: Attitude has a significant influence on the Intention to use AI.*

## 2.7 Awareness and Intention to Use AI

Awareness of AI-supported internal auditing is one of the main elements impacting auditors' intention to adopt this revolutionary technology, [44], [67], [68]. If auditors are well-versed about the potential, benefits, and range of applications of AI in the auditing industry, they are more likely to integrate the technology into their work, [69]. Faith in AI's intrinsic value is strengthened by this information, which cultivates a comprehensive awareness of its potential to boost accuracy, increase productivity, and offer profound analytical insights. Through AI, auditors may comprehend how to intricate auditing processes, minimise human error, and provide actionable intelligence, [70].

The significance of staying ahead of technological advancements to sustain competitiveness in the evolving auditing industry is real, [70]. However, a lack of knowledge could

result in hesitation and opposition since auditors might misjudge the advantages of AI or undervalue its complexity [69]. Raising awareness through certain education, rigorous training, and practical experience is essential to creating a strong willingness to employ AI in internal auditing. [44] found a correlation between awareness and the intention to use AI in services. Consequently, the following hypothesis may be proposed for this research:

*H5: Awareness has a significant influence on the Intention to use AI.*

### 2.8 Innovativeness and Intention to Use AI

According to [44] and [71], the degree of innovation in AI-supported internal auditing has a considerable effect on auditors' intention to use AI. [40] and [72] posited that auditors who perceive AI as a transformative technology that challenges conventional auditing paradigms are more likely to develop a strong intention to incorporate it into their activities. AI has become highly appealing because of the potential to introduce new approaches, streamline intricate processes, and yield deeper, data-driven insights surpassing the limitations of conventional approaches, [66]. This feeling of uniqueness stimulates auditors' interest and intellectual curiosity, which in turn motivates them to research and employ innovative techniques that enhance their professional abilities, [40].

According to [73], auditors who place a high priority on innovation are more likely to see AI as a strategic instrument that boosts productivity and guides increasingly challenging decision-making. However, auditors might not be persuaded or engaged if the revolutionary potential of AI is not sufficiently communicated, [70]. Highlighting the unique features of the technology and outlining its unique benefits is essential to igniting auditors' strong desire to use AI-supported auditing in their work. [44] found that the degree of innovation exhibited by AI-assisted robot advisers influences users' intentions to adopt AI. As a result, the following hypothesis might be proposed for this research:

*H6: Innovativeness has a significant influence on Intention to use AI*

## 3 Research Methodology

### 3.1 Participants and Sampling Design

To gather information about the adoption patterns of AI among auditors employed by various companies in Greater Jakarta, Indonesia (Jakarta, Bogor, Depok, Tangerang, and Bekasi), an online survey was utilised. Greater Jakarta is an essential option for data gathering sites due to its status as Indonesia's commercial and economic hub. Since these cities are home to several corporate offices, financial institutions, and auditing firms, they are ideal for studying the application of AI in auditing processes. Their advanced technological infrastructure and receptiveness to innovation further increase their significance. Furthermore, because of its diverse business landscape and substantial number of professional auditors, the region provides a typical sample for understanding the forces behind AI integration. These areas are a good representation to provide a more solid and practical applicability since it guarantees contextually relevant insights that are in line with Indonesia's socioeconomic and technical landscape.

This study employs a purposive sampling technique by targetting auditors specifically due to the limitation of an available sampling framework, [74]. Data was collected using a 6-point Likert scale, where 1 indicated strongly disagree and 6 indicated strongly agree. The process of gathering data was divided into two stages. First, the readability and clarity of the questionnaire were assessed through pre-testing. Five auditors from a large corporation and two professors from Jakarta contributed to this. Their input was taken into consideration, and the necessary adjustments were made. The revised questionnaire was then sent through various online channels, focusing on auditors who had never used AI for auditing before. During the two and a half months of data collection, 160 respondents were deemed suitable for further study.

A gender distribution of 46.2% females and 53.8% males was found in the data gathered (Table 2). A sizable percentage of responders (38.1%) were in the 28–43 age range. Only 56.3% of participants were working as auditors and had a bachelor's degree. Additionally, 40.6% of the participants worked in organizations with 30 to 300 people. In terms of work experience, 33.1% of the participants had been auditors for five to ten years. The majority of participants (37.5%) were general auditing personnel, despite the fact that they held a variety of jobs within their firms. Geographically, Tangerang accounted for the majority of participants (23.7%),

followed by Jakarta (22.5%), Depok (18.8%), and lastly Bogor and Bekasi (17.5%).

Table 2. Demographic profile of Respondents

| Item | Description | Freq. | %tage |
|---|---|---|---|
| Gender | Male | 86 | 53.80 |
| | Female | 74 | 46.20 |
| Age | 17 – 27 years | 25 | 15.60 |
| | 28 – 43 years | 61 | 38.10 |
| | 44 – 59 years | 55 | 34.40 |
| | 60 – 78 years | 19 | 11.90 |
| Last Level Education | Diploma degree | 27 | 16.30 |
| | Bachelor degree | 90 | 56.30 |
| | Master degree | 29 | 18.10 |
| | Doctoral degree | 15 | 9.30 |
| Number of Employees | Less than 10 employees | 16 | 10.00 |
| | 10 – 29 employees | 54 | 33.80 |
| | 30 – 300 employees | 65 | 40.60 |
| | More than 300 employees | 25 | 15.60 |
| Year of experience | Less than 5 years | 29 | 18.10 |
| | 5 until 10 years | 53 | 33.10 |
| | 11 until 15 years | 24 | 15.00 |
| | 16 until 20 years | 24 | 15.00 |
| | More than 20 years | 30 | 18.80 |
| Position in the Company | C Level / President | 17 | 10.60 |
| | Manager / General manager | 44 | 27.50 |
| | Supervisor | 39 | 24.40 |
| | Staff | 60 | 37.50 |
| Domicile of company | Jakarta | 36 | 22.50 |
| | Bogor | 28 | 17.50 |
| | Depok | 30 | 18.80 |
| | Tangerang | 38 | 23.70 |
| | Bekasi | 23 | 17.50 |

### 3.2 Measures

To assess the constructs in this study, a total of 24 items were modified from earlier research (Appendix A). Four questions to measure Perceived Usefulness were modified from the [19]. Likewise, three items also taken from [19] were chosen to gauge perceived ease of use. Four items for Attitudes were taken from the work of [75], while three items were taken from the studies of [37] and [75] to evaluate Sense of Trust. The three items used in this study to measure awareness were also provided by [44], from whom three questions for innovativeness were obtained. In order to investigate Intention to Use, four items were taken from [19] and [76]. The comprehensive inventory of these objects is shown in Appendix A.

### 3.3 Common Method Variance

The single-source data collected in this study tends to cause common method variance (CMV) issues. This occurs because it represents biases from the assessment technique rather than actual correlations between components. CMV is a serious issue in research using a Likert-scale approach for data collection. Inflating correlations as a result of biases including social desirability or acquiescence can lead to false results and threaten construct, internal and external validity. To enhance the accuracy and dependability of their findings, researchers resolve CMV by applying tactics including dividing measurements over time, maintaining anonymity, and using statistical methods like correlation matrix analysis and the Variance Inflation Factor (VIF). To address this potential issue, two methods were applied: correlation matrix analysis and collinearity assessment were conducted, [77]. According to [77], using the VIF to evaluate full collinearity should ideally be less than 3.3. These results indicated that CMV did not distort the study's findings; therefore, it still needs to be addressed to ensure the validity and trustworthiness of the research's conclusions. Reducing CMV enhances credibility and increase overall reliability and confidence in its conclusions.

## 4 Research and Findings

### 4.1 Measurement Model Results using PLS-SEM

For this study, the reliability and validity of the collected data were evaluated using PLS-SEM, [78], [79]. To confirm the validity and reliability, the measurement model was evaluated using four key parameters: average composite reliability, variance extracted, outer loading, and Cronbach's alpha. These parameters must all be greater than 0.7, 0.7, 0.7, and 0.5, respectively, [78], [80]. The results, displayed in Table 3, demonstrated that the data collected for each construct which is valid and accurate. Fornell and Larcker method (Table 4), recommended by [78], was used to assess discriminant validity.

### 4.2 Structural Model

Following the recommendations made by [81], this study conducted tests for multivariate skewness and kurtosis to assess the normality of the data distribution. The data did not exhibit multivariate normality, as evidenced by significant results for Mardia's multivariate skewness ($\beta$ = 250.94) and Mardia's multivariate kurtosis ($\beta$ = 904.16). In

accordance with [82], the study used a resampling bootstrapping method with 10,000 samples to determine path coefficients, standard errors, t-values, and p-values for the structural model, [83]. Additionally, the study took a complete approach, integrating p-values, confidence intervals, and effect sizes to assess the hypotheses in order to address concerns expressed by [84] regarding the limitations of depending only on p-values. Table 5 outlined the criteria used, ensuring a thorough and robust assessment of the research findings. According to the analysis' findings, perceived ease of use (PEOU), perceived usefulness (PU), and trust account with 72.8% of the variation (R2) in attitude (Figure 2). Additionally, 79.5% of the variance (R2) in the intention to use AI can be explained by attitude, awareness, and innovativeness.

Table 3. Construct reliability and Validity

| Constructs | Items | Loadings | CA | CR | AVE |
|---|---|---|---|---|---|
| Attitudes | ATT 1 | 0.932 | 0.942 | 0.942 | 0.851 |
| | ATT 2 | 0.929 | | | |
| | ATT 3 | 0.921 | | | |
| | ATT 4 | 0.907 | | | |
| Awareness | AWN 1 | 0.915 | 0.905 | 0.909 | 0.84 |
| | AWN 2 | 0.913 | | | |
| | AWN 3 | 0.921 | | | |
| Innovativeness | INO 1 | 0.922 | 0.914 | 0.916 | 0.853 |
| | INO 2 | 0.921 | | | |
| | INO 3 | 0.928 | | | |
| Intention to Use | ITU 1 | 0.922 | 0.939 | 0.939 | 0.844 |
| | ITU 2 | 0.919 | | | |
| | ITU 3 | 0.930 | | | |
| | ITU 4 | 0.904 | | | |
| Perceived Ease of Use | PEOU1 | 0.928 | 0.908 | 0.909 | 0.845 |
| | PEOU 2 | 0.919 | | | |
| | PEOU 3 | 0.911 | | | |
| Perceived Usefulness | PU1 | 0.914 | 0.933 | 0.934 | 0.832 |
| | PU2 | 0.917 | | | |
| | PU3 | 0.909 | | | |
| | PU4 | 0.909 | | | |
| Sense of Trust | SOT1 | 0.911 | 0.914 | 0.917 | 0.853 |
| | SOT2 | 0.925 | | | |
| | SOT3 | 0.934 | | | |

Table 4. Discriminant Validity (Fornell-Larcker)

| | ATT | AWN | INO | ITU | PEOU | PU | SOT |
|---|---|---|---|---|---|---|---|
| ATT | 0.922 | | | | | | |
| AWN | 0.785 | 0.917 | | | | | |
| INO | 0.757 | 0.786 | 0.924 | | | | |
| ITU | 0.863 | 0.803 | 0.771 | 0.919 | | | |
| PEOU | 0.783 | 0.807 | 0.764 | 0.824 | 0.919 | | |
| PU | 0.787 | 0.74 | 0.712 | 0.841 | 0.751 | 0.912 | |
| SOT | 0.810 | 0.785 | 0.798 | 0.874 | 0.802 | 0.837 | 0.924 |

Table 5. Path coefficients and confidence interval

| Relationship | Std. Beta | t-values | p-values | BCI LL | BCI UL | f2 | R2 |
|---|---|---|---|---|---|---|---|
| H1: PU→ATT | 0.283 | 2.510 | 0.006 | 0.098 | 0.466 | 0.083 | 0.728 |
| H2: PEOU→ATT | 0.310 | 3.003 | 0.001 | 0.147 | 0.482 | 0.118 | |
| H3: SOT→ATT | 0.325 | 2.756 | 0.003 | 0.139 | 0.529 | 0.089 | |
| H4: ATT→ITU | 0.543 | 6.648 | 0.000 | 0.399 | 0.667 | 0.477 | 0.795 |
| H5: AWN→ITU | 0.246 | 2.337 | 0.010 | 0.066 | 0.411 | 0.088 | |
| H6: INO→ITU | 0.166 | 1.665 | 0.048 | 0.005 | 0.333 | 0.045 | |

Table 5 provides a summary of the study's key findings and highlights significant relationships among the various constructs. The results show a strong correlation between perceived usefulness and attitude ($\beta = 0.283$, $t = 2.51$, $p<0.05$), supporting Hypothesis 1 (H1). Similarly, a correlation between Attitude and Perceived Ease of Use was found ($\beta=0.310$, $t = 3.003$, $p<0.05$), confirming Hypothesis 2 (H2). Additionally, the results confirm hypothesis 3 (H3) by demonstrating a statistically significant link between attitude and sense of trust ($\beta=0.325$, $t=2.756$, $p<0.05$). Furthermore, by demonstrating a substantial and significant correlation between attitude and intention to use AI ($\beta = 0.543$, $t = 6.648$, $p<0.05$), the results supported Hypothesis 4 (H4). Additionally, the study also supported H5 by confirming that Awareness is substantially linked with Intention to Use AI ($\beta=0.246$, $t=2.337$, $p<0.05$). Finally, the findings indicated a significant relationship between innovativeness and the intention to use AI ($\beta=0.166$, $t =1.665$, $p<0.05$) (Figure 2).

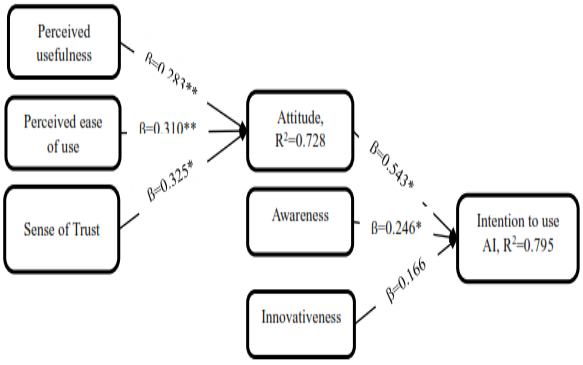


Fig. 2: Conceptual model result (**P<.01)

## 4.3 PLS-predict

PLS-Predict was presented by [85] as a mechanism for predicting the performance of a construct or item at the individual case level. This method evaluated a model's predictive relevance using a 10-fold procedure and a PLS-Predict measurement strategy, which worked especially well with sample sizes larger than 200. Their findings indicated that when PLS-RMSE values are consistently lower than the LM-RMSE values, the model has large predictive power. Predictive significance of the model is called into doubt if each PLS-RMSE value that exceeds its corresponding LM-RMSE value. On the other hand, moderating predictive potential is shown when the majority of PLS-RMSE values are lower. However, if only a few variables are lower, the model's predictive potential is small.

The PLS model's (PLS-RMSE) majority of errors are smaller than the LM model's (LM-RMSE), according to the study's findings in Table 6. This suggested that the model used in this investigation has a moderate predictive capacity.

Table 6. PLS-Predict

| Items | PLS-SEM (RMSE) | LM (RMSE) | PLS-LM | $Q^2$predict |
|---|---|---|---|---|
| ATT 1 | 1.207 | 1.220 | -0.013 | 0.544 |
| ATT 2 | 1.043 | 1.078 | -0.035 | 0.637 |
| ATT 3 | 1.188 | 1.287 | -0.099 | 0.559 |
| ATT 4 | 1.036 | 1.121 | -0.085 | 0.654 |
| ITU 1 | 1.009 | 0.998 | 0.011 | 0.675 |
| ITU 2 | 1.014 | 1.075 | -0.061 | 0.671 |
| ITU 3 | 0.995 | 1.059 | -0.064 | 0.674 |
| ITU 4 | 0.978 | 1.053 | -0.075 | 0.679 |

# 5 Discussion

AI integration is raising internal auditing procedures to new heights of accuracy and efficiency, revolutionizing internal auditing standards across sectors. Even with its promise, internal auditing has not fully embraced AI, particularly in developing nations like Indonesia. This study delves into the key factors shaping employees' adoption behavior toward AI in their internal auditing roles. To evaluate the strength and significance of the relationships between variables, the study employed effect size as a benchmark. Based on Cohen's guidelines, an f2 value between 0.02 and 0.14 indicated a small effect size, values from 0.15 to 0.34 represented a medium effect size, and 0.35 or above reflects a large effect size, [86]. This paradigm offers a clear lens through which to view the effects of many aspects impacting the adoption of AI, providing information about where to concentrate efforts in order to promote wider acceptance.

The results demonstrated that auditors' attitudes on utilizing AI in internal auditing are significantly influenced by the perceived usefulness of AI. The results indicated that auditors' attitudes towards utilizing AI in internal auditing are significantly influenced by the perceived usefulness (PU) of AI. This outcome is consistent with the result of [1], The subtle influence suggests that only a trivial percentage of the variation in auditors' views may be explained by perceived usefulness. Although essential, it is not the major aspect. This implies that perceived usefulness is one of the major components that shape auditors' perceptions. In other elements, perceived ease of use, auditors' innovative thinking, or confidence in AI systems, might have a stronger or complementary impact. This emphasizes the importance of a multifaceted approach when pursuing the influence of auditors' attitudes. While enhancing the perceived usefulness of AI tools is important, It may not be enough on its own to yield substantial changes in attitudes. Organizations also need to focus on enhancing trust in AI systems, reducing perceived complexity, and addressing other related factor to maximize the impact.

The result of this study also highlights that auditors' positive opinions towards AI in internal auditing were significantly increased by perceived ease of use (F2 = 0.118). [15] pointed out that a major factor in the acceptability of AI services is the ease of use. However, the subtle effect observed in our study emphasized that while ease of use is important, it is not the major factor that shaping positive attitudes.

This study reveals that auditors' positive attitudes towards AI in internal auditing are significantly influenced by trust (f2 = 0.089). This result aligns with [10], who found out that the sense of trust is a key component in fostering a positive attitude towards AI. This implies that, while sense of trust play an important role in shaping auditors' attitudes, its impact is relatively modest as compared to other factors.

Furthermore, a subtle effect indicated that sense of trust is just one of several elements that influencing the way auditors perceive AI. Considering that it helps allay auditors' fears and doubts about utilizing AI for delicate task like internal auditing, trust is essential. Auditors tend to have a favorable opinion of AI tools that they are certain in its dependability, accuracy, and moral application. This study also indicates how crucial it is for company to address critical problems such as data security, system reliability, and ethical transparency in order to develop auditors' sense of trust in AI systems when perform internal auditing. Although developing a sense of trust is important, it should be considered as a part of a broader strategy that improve the perceived value and utility of AI products.

This study highlighted that auditors' attitudes have a decisive impact on their intention to use AI to perform internal auditing (f2 = 0.477). This result aligns with [15], who emphasized that a major factor in influencing AI adoption is consumers' pre-adoption attitudes regarding the technology's prospective advantages. This major effect indicates a strong relationship between auditors' attitudes and willingness to adopt AI in internal auditing. This means the auditors' attitudes are a major factor in determining their decision to utilize or not.

These factors define the auditor perspective on AI's potential to enhance their performance. When attitudes are defined by these beliefs, a positive shift

in attitudes tends to have stronger intention to use AI in auditing practices. Given the major effect, this finding highlights the essential of addressing auditors' attitudes toward AI adoption strategies. Organizations can focus on enhancing these attitudes by offering training, showcasing the benefits of AI tools, and resolving reservations regarding their application to encourage the AI adoption. Fostering a positive perception of AI in internal audits is crucial, as attitude has a significant impact on AI adoption.

Moreover, despite the minor effect ($f2 = 0.008$) on this study, the auditors' awareness of AI increases their intention to use it to perform internal auditing. This result is align with the previous research of [44], who highlighted the critical role of awareness in motivating the intention to adopt AI. The auditors imply that they are tends to use AI technology into the workflows as they become more familiar with it. From this perspective, awareness includes understanding AI tools, their features, and the possible advantages could offer auditing procedures. However, although awareness plays a crucial role, it is not the primary factor influencing auditors' intentions, as illustrated by the subtle effect.

Finally, although the effect is subtle ($f2=0.045$), the study indicated that auditors' intention to use AI in internal auditing is positively influenced by its innovativeness. This validates the findings of [44], who highlight the innovative nature of AI increases the likelihood service operations will adopt it. In this context, AI's "innovativeness" refers to conventional techniques, such as automation, machine learning, and predictive analytics. By providing previously unachievable insights, increased accuracy, and increased efficiency, these features could encourage auditors.

# 6 Research Implications

## 6.1 Theoretical Implications

This research introduces a new perspective regarding AI's role in internal auditing in underdeveloped countries including Indonesia, using Extended Technology Acceptance Model (TAM). This emphasizes that perceived usefulness, perceived ease of use, and sense of trust have a significant positive effect on attitudes towards the intention to use AI in internal auditing. Thus, this research provides a foundation for further research on AI adoption in internal auditing.

This research also indicated that attitude, awareness, and innovativeness support the intention of employees to use AI, with attitude being the major factor ($\beta=0.543$). This highlights the major impact on the acceptance or rejection of AI-supported internal auditing based on people's attitudes.

## 6.2 Managerial Implications

This study has examined some of the research's practical implications. First, the results demonstrated that Perceived Usefulness, Perceived Ease of use, and Trust have a significant effect on auditors' intention to use AI in internal auditing which means that internal auditors can use AI technology to increase accuracy, efficiency and facilitate a more seamless AI integration and increase staff adoption of the technology. Better judgements can be made by shareholders and investors thanks to developments in AI-driven auditing. Likewise, audit firms and organizations can use this information to enhance their change management strategies and encourage the adoption of AI by emphasizing its benefits.

# 7 Limitations and Future Research

This study acknowledges some limitations. First, the response rate for the online survey distributed was 27.7% due to time and financial restrictions Second, this research demographic was limited to Jabodetabek area in Indonesia. Future research can be expanded to a vaster area to provide a better understanding of how AI is implemented in internal auditing processes.

# 8 Conclusion

AI in internal auditing is changing the way auditors analyze, appraise, and guarantee adherence to organizational procedures and documentation. Internal auditing is moving from conventional, sample-based methods to thorough, real-time, and predictive studies by utilizing machine learning, data analytics, natural language processing, and other AI tools. AI's ability to process large volumes of data quickly gives auditors a big edge in auditing since it makes it possible to identify errors, irregularities, and possible fraud with greater accuracy. By reducing human error and facilitating a proactive approach, this real-time monitoring helps to discover issues before they become more serious. By giving auditors relevant insights from data patterns and trends, AI also improves decision-making by allowing them to concentrate on high-risk areas and make strategic recommendations.

Additionally, by maintaining systems in line with regulatory requirements, AI helps to ensure compliance with changing rules. However, integrating AI into internal auditing requires balancing sense of trust and technical knowledge, as auditors need to interpret AI findings accurately and maintain transparency. While AI offers remarkable efficiency and accuracy, it introduces ethical and operational considerations, as well as data security, privacy, and the need to understand AI's limitations and potential biases. Therefore, artificial intelligence (AI) strengthens internal controls, governance, and risk management by giving auditors sophisticated tools to navigate complicated corporate environments and improving audit quality and efficiency.

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During the preparation of this work the authors used Grammarly in order to improved English grammar. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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- A. Gui writing introduction, literature review, methodology, data collection, result & discussion, and conclusion.
- S. Hasnan contributed to research implication and limitation part, review and editing.
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# APPENDIX

Table 1. Review of Previous Research

| Source | Purpose of the study | Sample types | Significant findings | Geographic location |
|---|---|---|---|---|
| [33] | To investigate the influence of AI and Industry 4.0 readiness, on the effectiveness of accounting and auditing operations. | Auditors | Big data analytics and deep learning advancements can improve accounting and auditing practices. | Saudi Arabia |
| [25] | To explore the perspectives of auditors in the UAE regarding the use of AI | Auditors | Local and multinational audit companies' perceptions of AI's contribution to audit quality diff insignificantly. | United Arab Emirates |
| [40] | To investigate the relationship between accounting students' degree of technological readiness and their decision to embrace AI in term of perceived utility and perceived ease of usage. | Accounting Students | PEOU and PU mediate association between the readiness of technology and AI adoption intention. | The USA |
| [38] | To understand the factors influencing internal auditors' behavioral intentions regarding CAATs adoption | Auditors | PEOU, PU, social and organizational influences, facilitating conditions, trust, satisfaction have influence on CAATs adoption | Saudi Arabia |
| [45] | To examine the impacts of emerging technology on accounting professionals' practice of auditing. | Accounting professionals | Technology adoption, technological challenges and ease of use are the antecedents influence on auditing practice of accounting professionals. | India |
| [9] | To study the elements affecting the use of AI in information auditing. | Auditors | The intention to adopt information audit technology is positively influenced y internal factors. | Egypt and Jordan |