Journal of Theoretical and Applied Information Technology
31st January 2025. Vol.103. No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

THE ROLE OF AI ADOPTION IN ACHIEVING SUSTAINABLE AUDIT QUALITY

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ABSTRACT

The audit profession plays a crucial role in ensuring financial transparency, with the adoption of Artificial Intelligence (AI) offering significant potential to enhance audit quality. This study investigates factors influencing AI adoption among auditors in achieving sustainable audit quality using the Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. A quantitative approach was applied, collecting data from 130 auditors in Indonesian public accounting firms via questionnaires. Data analysis utilized Structural Equation Modelling-Partial Least Squares (SEM-PLS) using smartPLS. The findings indicate that Facilitating Conditions and Habit significantly influence AI adoption, while factors such as Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Price Value are statistically insignificant towards AI adoption. Additionally, the adoption of AI significantly impacts sustainable audit quality by improving efficiency, reducing errors, and enhancing reliability. These results highlight the need for infrastructure support and habitual use to drive AI adoption among auditors.

Keywords: *Artificial Intelligence, Sustainable, Audit, Quality, UTAUT2, SEM-PLS*

1. INTRODUCTION

1.1 Research Background

The audit profession is a critical pillar supporting financial integrity and transparency in the global economy. As business environments evolve and become increasingly complex, the need for efficient and accurate auditing practices has never been more pressing. One of the most promising advancements in this field is the adoption of Artificial Intelligence (AI). AI has the potential to revolutionize auditing by enhancing the accuracy, reliability, and timeliness of audit processes.

Traditionally, auditing has relied heavily on manual processes and human judgment. However, these methods are increasingly challenged by the complexity of modern financial transactions, stringent regulatory demands, and the overarching need for greater transparency. In response to these challenges, AI technologies have begun to gain traction within the auditing profession. Several major audit firms have announced plans to invest billions of dollars in AI audit applications [1]. Among these firms, the Big 4 Accounting firms are, as expected, at the forefront of revolutionizing the use of AI in the field of accounting and auditing. The Big 4's adoption of AI technologies reveals two notable trends: the increasing investment in AI within the accounting industry and the emphasis on AI's crucial role in the future success of the field [2]. AI can process large volumes of data with speed and precision far surpassing human capabilities [3]. For instance, AI algorithms can identify patterns and make predictions from large amounts of data, tasks heavily relied upon by auditors [4].

The importance of audit quality is immense, as it forms the foundation for the credibility of financial statements and, consequently, the trust stakeholders place in financial markets. However, achieving sustainable audit quality remains a challenge due to various factors such as human error, resource constraints, and the ever-evolving nature of regulatory requirements. AI has the potential to mitigate these challenges by enhancing the precision and scope of audit activities, thus contributing to the overall integrity and transparency of financial reporting.

A primary factor behind the increasing relevance of AI in auditing is its ability to handle large volumes of data with speed and accuracy. Traditional auditing methods, which rely heavily on manual sampling and checks, are often time-consuming and prone to errors [5]. In contrast, AI algorithms hold significant promise for enhancing efficiency, minimizing errors, and allowing accountants and auditors to concentrate on more complex and valuable tasks rather than spending time on repetitive, time-consuming, and rule-based activities [6]. The adoption of AI in auditing is also driven by the need to enhance audit sustainability. Sustainable audit quality involves maintaining high standards of accuracy and reliability over time, despite changes in business environments and regulatory landscapes. AI can support this by providing consistent and scalable solutions that adapt to new audit requirements and emerging risks. For instance, machine learning models can be trained to recognize patterns and trends in financial data, enabling auditors to predict and respond to potential issues before they escalate.

Numerous studies have explored the impact of technology on audit quality, highlighting both opportunities and challenges. For example, one study in 2023 concluded that AI enhances audit efficiency and accuracy but requires significant investment in technology and training [7]. Similarly, another study in 2024 found that AI can improve productivity and engagement in auditing, although the core functions of confidence and assurance will remain unchanged [8]. Additionally, the replacement of human beings with AI in auditing should be approached cautiously, even though the benefits of AI implementation surpass those of manual auditing. Effective AI implementation in auditing needs to be used in conjunction with human intervention rather than entirely replacing humans with AI [9]. These studies underscore the transformative potential of AI while also pointing to the need for careful implementation and management.

Despite the clear advantages, the adoption of AI in auditing is not without its challenges. High implementation costs, the need for specialized skills, and concerns over data privacy and security present significant barriers [4]. Moreover, there is a notable gap in existing research regarding the long-term impact of AI adoption on sustainable audit quality. Most studies, such as those conducted by Noordin [10] and Rikhardsson [11], focus on short-term improvements and specific applications of AI, without addressing how these advancements can be sustained over time and across different auditing contexts. This gap highlights the need for comprehensive research that examines the integration of AI into auditing practices, its implications for audit quality sustainability, and the strategies required to maximize its benefits.

This study aims to fill these gaps by exploring how AI adoption impacts the efficiency and effectiveness of audit processes and identifying the factors influencing its acceptance and use within the auditing profession through the UTAUT 2 framework. By employing Unified Theory of Acceptance and Use of Technology (UTAUT) 2 model, which includes a broader set of variables compared to UTAUT, this research will provide a more comprehensive understanding of the drivers and barriers of AI adoption and its implications for audit quality sustainability.

1.2 Research Problem Formulation

The use of AI into auditing methods is a rapidly developing subject of study with enormous promise for improving audit quality and efficiency. Despite the promising developments that AI provides, understanding the factors driving its adoption and influence on audit quality remains an important topic of research. This study aims to investigate these characteristics using the UTAUT 2 framework, which provides a complete model for assessing technological acceptability.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The research problem formulation is centered around eight key questions that will guide the investigation and form the basis of the hypotheses in Chapter 2. These questions are designed to uncover the dynamics between various factors and AI adoption in audit processes, as well as the subsequent effects on sustainable audit quality. The specific research problems addressed in this study are as follows:

1. How does Performance Expectancy influence the adoption of AI in audit processes?
2. How does Effort Expectancy influence the adoption of AI in audit processes?
3. How does Social Influence affect the adoption of AI in audit processes?
4. How do Facilitating Conditions influence the adoption of AI in audit processes?
5. How does Hedonic Motivation influence the adoption of AI in audit processes?
6. How does Price Value influence the adoption of AI in audit processes?
7. How does Habit influence the adoption of in audit processes?
8. How does the adoption of AI impact sustainable audit quality?

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Technology Acceptance Model

In the past, to explain and forecast consumer adoption and use of information technology (IT), researchers have developed and tested several competing models, including the technology acceptance model (TAM) as well as models based on the theory of planned behavior (TPB) [12].

In 2003, Venkatesh synthesized 8 prominent models of IT acceptance to develop a unified model that integrates elements from each of these prominent models of IT adoption [13]. This unified model is called the unified theory of acceptance and use of technology (UTAUT). In organizational contexts, UTAUT identifies four key factors/constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderators (age, gender, experience, and voluntariness) that are related to predicting behavioral intention to use a technology and actual technology use. UTAUT states that whereas behavioral intention and facilitating conditions govern technology usage, performance expectancy, effort expectancy, and social influence were theorized and found to influence behavioral intention to utilize a technology [14].

As consumer technologies became more prevalent, the UTAUT model was adapted to focus on the intrinsic motivation of technology users. Thus, in 2012, the original UTAUT was expanded to include three new constructs: hedonic motivation, price value, and habit, resulting in the updated version known as UTAUT2. However, since customers lack an organizational mandate and frequently choose their own behavior, voluntariness of usage was removed as a moderator in UTAUT2. The variance explained in behavioral intention (56–74%) and technology use (40–52%) was significantly improved by UTAUT2 in comparison to UTAUT [15]. Thus, it makes sense to use this model to research the impact of AI adoption In achieving sustainable audit quality.

2.2 Effect of Performance Expectancy to Auditor AI Adoption

Performance expectancy (PE) is defined as the degree to which an individual believes that employing a specific system would help them achieve better job performance [13]. In the context of AI adoption in auditing, the authors predict that auditors expect AI to enhance their auditing capabilities, such as improving accuracy, detecting anomalies, and reducing manual effort. According to a research conducted by Albawwat in 2021, the more the auditors perceive AI as beneficial to their performance, the more likely they are to adopt it [16]. Based on this discussion, the hypothesis developed in this study is:

H1: Performance expectancy has a significant effect on auditor AI adoption

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.3 Effect of Effort Expectancy to Auditor AI Adoption

Effort Expectancy (EE) refers to the ease of usage of a given system [13]. In the context of AI adoption in auditing, the authors predict that when auditors find AI tools intuitive and user-friendly, they are more inclined to integrate them into their work[17]. Conversely, if the technology is perceived as complex or difficult to use, its adoption may be hindered.

According to research conducted by Rikhardsson in 2022 [11], EE is a significant factor in the adoption of AI in the auditing context. If auditors perceive AI as requiring a high level of effort to learn and use, it could negatively impact their intention to adopt the technology. Conversely, if the effort expectancy is low, particularly among younger and lower-level auditors who are more likely to be open to learning new technologies, the adoption of AI in auditing could be more favorable. Additionally, according to Albawwat [16], the ease of use of AI technologies is a critical factor in auditor acceptance. Even when such technologies are beneficial to their companies, auditors are far less likely to use them if they do not feel comfortable using them. Based on this discussion, the hypothesis developed in this study is:

H2: Effort expectancy has a significant effect on auditor AI adoption

2.4 Effect of Social Influence to Auditor AI Adoption

Social influence (SI) is the level to which an individual perceives that important individuals feel they should utilize a new technology [13]. Luca Ferri in 2023 showed that SI has a positive effect on risk professionals' intention to implement AI [18]. In the context of AI adoption in auditing, the authors predict that auditors may experience endorsement or encouragement from colleagues and managers to adopt AI tools. Based on this discussion, the hypothesis developed in this study is:

H3: Social influence has a significant effect on auditor AI adoption

2.5 Effect of Facilitating Conditions to Auditor AI Adoption

Facilitating Conditions (FC) are the extent to which an individual feels that an organizational and technological infrastructure exists to enable the usage of a new system [13]. In the case of AI adoption in auditing, the authors predict that when support facilities such as the availability of knowledge, software and hardware are available to implement the AI tools, the auditor's desire to utilize them will increase. Conversely, when auditors do not have access to the necessary facilities, their desire to employ AI techniques will decrease.

According to Seethamraju, for AI adoption to be effective, auditing firms need to invest in separate labs/units to create AI-based solutions, or form multi-disciplinary teams that include AI and data analytics professionals as well as traditional auditors [19]. This suggests that the existing organizational structure, as well as the willingness to adjust it, are critical for the successful integration of AI into the audit process. Based on this discussion, the hypothesis developed in this study is:

H4: Facilitating conditions has a significant effect on auditor AI adoption

2.6 Effect of Hedonic Motivation to Auditor AI Adoption

Hedonic Motivation (HM) refers to the enjoyment or pleasure derived from using a technology [15]. In the context of AI adoption, the author predicts that auditors who find AI tools engaging and enjoyable to use may be more motivated to integrate them into their audit processes. This positive emotional response can enhance the overall adoption rate of AI technologies. According to Rikhardsson's study, auditors believe that using AI will increase their performance and make their jobs more exciting [11]. They expect AI to become essential in auditing organizations, and they do not appear concerned about AI replacing auditors. This is because they believe that the nature of auditing services may change, but the basic product—trust and assurance—remains constant. Based on this discussion, the hypothesis developed in this study is:

H5: Hedonic motivation has a significant effect on auditor AI adoption

2.7 Effect of Price Value to Auditor AI Adoption

Price Value (PV) is the cost-benefit evaluation associated with adopting a new technology [15]. In auditing, the perceived value of AI adoption is influenced by the costs of implementation, maintenance, and training against the expected benefits, such as increased efficiency and improved audit quality. When auditors perceive that the benefits of AI outweigh the costs, they are more likely to adopt the technology.

Aitkazinov, in his 2023 study concluded that the potential for AI technologies to save time can result in lower costs and more efficient audit procedures [7]. Greenman's 2017 study also verified that AI is being utilized in auditing to help reduce costs by automating tasks that have traditionally been performed manually by human auditors [20]. This automation leads to increased efficiency, as AI technologies can process large amounts of data at a much faster rate than humans. Furthermore, AI's ability to learn from sample documents and identify key terms automatically streamlines the document review process, which is another area where auditors can save time and reduce costs. With these studies in mind, the authors predict that auditors will be more inclined to perceive that the benefits from adopting AI in auditing outweighs its cost. Based on this discussion, the hypothesis developed in this study is:

H6: Price value has a significant effect on auditor AI adoption

2.8 Effect of Habit to Auditor AI Adoption

Habit (H) is the extent to which individuals tend to perform behaviors automatically because of learning [15]. In the context of AI adoption, the authors predict that auditors who have developed a routine or familiarity with AI tools may continue to use them consistently, thereby reinforcing their adoption over time. Habitual use of AI can lead to deeper integration of the technology into auditing practices. Turner & Cacciatori, in their 2016 study [21] posits that habit can be divided into a typology with varying levels of automation and deliberation, which are:

- Automatic Habit: Activities performed under stable conditions with minimal reflexivity.
- Infused Habit: Flexible habits infused with thought, requiring adaptability and deliberation.
- Contested Habit: Requires some deliberation to inhibit repetition even in stable conditions.
- Skillful Habit: Actions performed under unstable conditions with low reflexivity but requiring intelligence and understanding.

Levinthal and Rerup, meanwhile, emphasizes the interdependence between “mindful” and “routine” work, where structured routines can act as a foundation for handling new and complex problems [22]. Routine actions often involve elements of mindfulness, and routine monitoring systems are crucial for organizational reflexivity and adaptation.

Samiolo then expands upon these concepts, stating that the adoption of AI in auditing both challenges and enhances the balance between routine and mindfulness [23]. While automation might push auditors toward more "automatic habits," it also has the potential to elevate them into "infused habits," where higher-order thinking, adaptability, and deliberation come into play. This interplay means that AI adoption can either erode or expand the scope of auditors’ judgment, depending on how auditors adapt their habits to engage with these technologies critically and thoughtfully. Based on this discussion, the hypothesis developed in this study is:

H7: Habit has a significant effect on auditor AI adoption

2.9 Effect of auditor AI Adoption to Sustainable Audit Quality

Following the validation of the seven variables above, the subsequent phase involves validating the key measure of AI adoption's impact on sustainable audit quality. This process is crucial to confirm that AI adoption not only affects auditors' decisions to utilize the technology but also makes a

Journal of Theoretical and Applied Information Technology
31st January 2025. Vol.103. No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

meaningful contribution to improving the overall quality of audits over time.

Hasan, in his 2022 study states that AI adoption offers the potential to hold significant promise for enhancing efficiency, minimizing errors, and allowing accountants and auditors to concentrate on more complex and valuable tasks rather than spending time on repetitive, time-consuming, and rule-based activities [6]. These benefits directly contribute to the sustainability of audit quality (SAQ), as AI-driven auditing accompanied by a move towards a leaner process: audit firms that invest in AI are able to lower the fees they charge while reducing their audit workforces and showing increased productivity, as measured by total fees per employees [4]. Based on this discussion, the hypothesis developed in this study is:

H8: The adoption of AI has a significant effect on sustainable audit quality

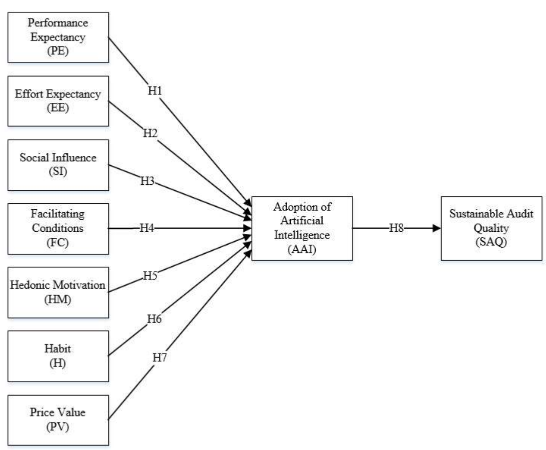

Figure. 1: Research framework adapted from Unified Theory of Acceptance and Use of Technology (UTAUT) 2 model

3. RESEARCH METHODOLOGY

3.1 Research Method

This study uses a quantitative research approach, defined as using collected numerical data to analyze and examine correlations between variables, followed by the use of statistical methodologies. Therefore, the variables used in this study will be selected in such a way that they can produce questions as measurements that will produce numerical data to be analyzed and to assess the proposed hypothesis [24]. Primary data for this study will be gathered by surveys, using questionnaires specifically tailored to the variables and hypotheses under investigation. The questions will be based on the key indicators for each variable. This questionnaire will be created using Google Forms and then distributed to auditors working in public accounting firms located in Indonesia that reflect the study's population. Considering that the population size cannot be estimated precisely since there is ambiguity in the number of auditors working in public accounting companies due to significant employee turnover, this study will follow the approach given by J. F. Hair [25], who suggests that the unknown population should be at least ten times the number of variables. As a result, it is agreed that 143 persons will be the number of responses.

To measure the variables of performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, habit, adoption of AI, and sustainable audit quality, the questionnaire will use a five-point Likert scale, with 5 representing "strongly agree" and 1 representing "strongly disagree”.

There will be two types of non-probability sampling methods used: snowball sampling and convenience sampling. Convenience sampling is a technique for gathering samples by having respondents pass or recommend the researcher's questionnaires to other possible respondents, from whom data would be gathered thereafter. Because of this ongoing process, the sample size will progressively enlarge like a snowball rolling down a hill [26]. Convenience sampling, on the other hand, uses respondents who are approachable and have access to the researcher to gather samples. For this reason, this approach is deemed to be less costly and labor-intensive as other sampling methods [27].

For data analysis, this study employs Structural Equation Modelling Partial Least Square (SEM-PLS). The SEM-PLS method is chosen due to its ability to handle complex models with multiple variables and its suitability for studies with smaller sample sizes [28]. The data processing will be carried out using SmartPLS 4 software [29], the latest version available, which offers enhanced capabilities for conducting SEM-PLS analyses. The data for this research is available online on: https://binusianorg-my.sharepoint.com/personal/bambang_handoko_binus_edu/_layouts/15/guestaccess.aspx?share=EatH5hdxXJVLkshJjsMpwnEBjz96-9O96zUtPbiFZU2o2Q&rtime=v6PeCxUk3Ug

3.2 Operation of Variables

Operationalization of the variables used to define the variables subjected to tests or measurements according to predetermined standards. Table 1 will present an operationalization of variables to facilitate quantitative assessment of this study.

Table 1. Operation of Variables

Variable	Key Indicator	Source
Performance Expectancy (PE)	1. AI can enhance the speed of auditors' work completion 2. Improve auditors' productivity 3. Increase chance of auditors to receive a raise	[8], [30]
Effort Expectancy (EE)	1. Ease of learning the usage techniques of the new AI enhanced system 2. Straightforwardness of using the system 3. Time required for auditors to learn the new system	[8], [31]
Social Influence (SI)	1. Key persons in the organization encourage the use of the system 2. Level of support the organization's senior management shows regarding the system's implementation 3. Auditors are influenced by colleagues who suggest to them in using AI for their work	[8], [32]
Facilitating Condition (FC)	1. Auditors feel they have everything needed to operate the system 2. Auditors have a sense of familiarity with running the system 3. Availability of a person dedicated to readily assist with any system issues	[8]
Hedonic Motivation (HM)	1. Auditors feel that using AI makes their work more enjoyable 2. Auditors feel that using AI in their work helps keep them interested 3. Auditors feel that using AI in their work is inspiring	[32], [15], [33]
Price Value (PV)	1. Auditors feel that the benefits of using AI outweigh its costs 2. Auditors feel that utilizing AI is reasonable in terms of money and time spent 3. AI utilization in auditing provides good value	[32]
Habit (H)	1. Auditors feel that using AI for assisting audit purposes has become a daily occurrence for them 2. Auditors use AI for assisting audit purposes without hesitation 3. Auditors feel that they have to use AI in their work	[34], [15], [33]
Adoption of AI (AAI)	1. Auditors are prepared to use AI technology in their audit tasks. 2. Firms are prepared to modernize their audit platforms and use AI in them.	[35], [35]
Sustainable Audit Quality (SAQ)	1. AI enhances auditors' professional skepticism and judgment in critical areas 2. AI enables comprehensive and continuous risk assessment 3. AI ensures precision in audit processes, reducing human errors, and increasing reliability	[8]

4. RESEARCH RESULT AND DISCUSSION

4.1 Identity of Respondents

For this study, a questionnaire was developed and distributed to a total of 143 respondents, all auditors employed by Indonesian public accounting firms. After reviewing the responses, 13 outliers with excessively fluctuating answers were excluded, leaving a final sample of 130 respondents. This sample size meets the minimum respondent requirement, following Joseph Hair's [25] guideline of at least five times t0he number of indicators used. The questionnaire collected demographic information, including respondents' age, gender, position, and years of work experience. A summary of this data is provided in the table below:

Table 2. Identity of Respondents

Characteristics	*n*	%
Gender		
Male	60	46.2%
Female	70	53.8%
Age		
21 - 30 years	110	84.6%
31 - 40 years	18	13.8%
41 - 50 years	2	1.5%
Position		
Associate Auditor	84	64.6%
Senior Associate Auditor	31	23.8%
Manager/Supervisor Auditor	13	10.0%
Partner	2	1.5%
Work Experience		
1 - 5 years	101	77.7%
6 - 10 years	24	18.5%
10 - 15 years	3	2.3%
> 15 years	2	1.5%

The data presented in Table 2 indicates that the majority of respondents are female, aged between 21 and 30, holding positions as associate auditors in public accounting firms. Most have between 1 to 5 years of professional experience. This demographic information was gathered from the initial four questions in the survey, while subsequent sections focus on variables' indicators. Relationships among both exogenous and endogenous variables are modeled structurally and will be analyzed using the Partial Least Squares (PLS) approach on SmartPLS 4. The following sections discuss the findings from these analyses in detail.

4.2 Outer Loading Test

Our questionnaire underwent an outer loading test to confirm that each indicator effectively represents its respective variable. This process ensures that indicators accurately capture the construct they're intended to measure. If an indicator has a value below 0.5, it is removed to maintain measurement accuracy [36].

For applied research, such as this study on auditor perceptions, Imam Ghazali's [37] literature on PLS suggests that values between 0.5 and 0.7 are acceptable, as the focus is on applying existing theories rather than developing new ones. In our initial sample of 143 respondents, certain indicators fell below the 0.4 threshold due to fluctuations in responses. For example, the indicator SI3 had a low outer loading value of only 0.195 (<0.4), which made it unsuitable. However, after excluding responses from 13 outliers and focusing on the remaining 130 respondents, all indicators met the minimum threshold of 0.5, so no indicators needed to be excluded from the final analysis.

Table 3. Outer Loading Value

Indicator	Loading	Indicator	Loading
AAI1	0.902	PE1	0.839
AAI2	0.717	PE2	0.814
EE1	0.828	PE3	0.694
EE2	0.763	PV1	0.881
EE3	0.807	PV2	0.930
FC1	0.877	PV3	0.896
FC2	0.669	SAQ1	0.870
FC3	0.901	SAQ2	0.924

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

H1	0.865
H2	0.881
H3	0.854
HM1	0.914
HM2	0.912
HM3	0.817
SAQ3	0.885
SI1	0.935
SI2	0.946
SI3	0.631

4.3 Validity and Reliability Test

To ensure the accuracy and consistency of the measurement tools in this study, both validity and reliability tests were performed. These tests are crucial to confirm that the research findings are both precise and valuable [38]. Both validity and reliability must be satisfied; achieving one without the other does not guarantee robust measurements. Validity assesses how well an instrument captures the intended construct, while reliability checks the stability and consistency of the results [39].

Validity is divided into convergent and discriminant validity. Convergent validity examines the degree to which indicators related to the same construct are aligned. This is assessed using the Average Variance Extracted (AVE), where a threshold of 0.5 or higher indicates that the latent construct explains more than half of the variance in its indicators [40]. Additionally, for reliability, test composite reliability (rho_c) is used to verify the internal consistency of the constructs, with values between 0.6 to 0.7 or higher considered acceptable [36]. In this study, all indicators met the required convergent validity, with AVE values exceeding 0.5, and reliability test, with composite reliability values (rho_c) surpassing the 0.7 threshold, as presented in Table 4.

Table 4. Composite Reliability and Average Variance Extracted

Variable	AVE	Composite reliability (rho_c)
AAI	0,663	0,795
EE	0,640	0,842
FC	0,677	0,861
H	0,752	0,901
HM	0,778	0,913
PE	0,616	0,827
PV	0,814	0,929
SAQ	0,798	0,922
SI	0,723	0,883

Discriminant validity refers to the degree to which measurements of different constructs are distinct and not correlated with each other. It can be assessed using the Fornell-Larcker criterion, which involves verifying that the square root of the Average Variance Extracted (AVE) for each construct is greater than its correlation with other constructs [40]. As shown in Table 5, the square root of the AVE for each construct (on the diagonal) is higher than its correlations with other constructs (off-diagonal), indicating no issues with discriminant validity.

These validity tests play a crucial role in confirming whether the measurement instruments accurately capture the intended constructs. A valid test demonstrates a robust causal relationship between the independent and dependent variables, while also ensuring that irrelevant variables are excluded. These tests address potential validity threats, such as when the measurement tool fails to comprehensively cover a construct or selectively measures only part of it.

Table 5. Fornell-Larcker Criterion

	AAI	EE	FC	H	HM	PE	PV	SAQ	SI
AAI	0,8								
EE	0,5	0,8							
FC	0,7	0,4	0,8						
H	0,7	0,5	0,4	0,9					
HM	0,4	0,3	0,5	0,4	0,9				
PE	0,5	0,4	0,5	0,5	0,4	0,8			
PV	0,7	0,5	0,6	0,6	0,4	0,4	0,9		
SAQ	0,7	0,5	0,5	0,7	0,4	0,5	0,7	0,9	
SI	0,4	0,2	0,7	0,2	0,4	0,5	0,3	0,2	0,9

4.4 Coefficient Determination Test

Once the validity and reliability of the construct measures have been established, the next phase entails evaluating the results of the structural model (inner model). A measure for the predictive ability of the model and the correlation between the constructs is the coefficient of determination [36]. The construct of auditors' adoption of AI has an adjusted R-Square value of 0.660, as shown in table 6. Accordingly, this shows that PE, EE, SI, FC, HM, H, and PV can all contribute up to 66% to auditors' AI adoption, with the remaining 34% being influenced by variables outside the purview of this study. As for the construct of sustainable audit quality, the adjusted R-Square value of 0.541 in table 6 shows that the adoption of AI by auditors can contribute up to 54% to sustainable audit quality, with the remaining 46% being influenced by variables outside of the scope of this study.

Table 6. Coefficient of Determination

	R-square	R-square adjusted
AAI	0,663	0,660
SAQ	0,542	0,541

4.5 Hypothesis Testing

The path coefficients for structural model relationships that reflect the hypothesized relationships between the constructs are obtained after the PLS-SEM algorithm has been run. The standard error that determines the t-values and *p* values for each path coefficient is then obtained by performing the hypothesis testing using SmartPLS's resampling bootstrapping procedure. Acceptance of the alternative hypothesis occurs when the t-statistic exceeds the t-table value, and vice versa. Under the assumption that the significance level is 5%, the alternative hypothesis is accepted when the *p* value is less than 0.05. The two-tailed test in this study has a critical value of 1.96 and a significance level of 5%. Simply put, if the t-statistic is more than 1.960 and the *p* value is equal to or less than 0.05, then one variable can be said to have a significant effect on the other variable, and the null hypothesis should be rejected [41].

Table 7. Hypothesis Testing

Hypothesis	Original Sample	T Statistics	P values
H1: PE → AAI	0,035	0,484	0,629
H2: EE → AAI	0,066	0,969	0,333
H3: SI → AAI	-0,047	0,623	0,533
H4: FC → AAI	0,394	4,328	0,000
H5: HM → AAI	-0,024	0,374	0,708
H6: H → AAI	0,430	4,817	0,000
H7: PV→ AAI	0,123	1,239	0,215
H8: AAI → SAQ	0,736	18,507	0,000

As shown in table 7, eight hypotheses have been tested. According to the test's results, the only variables that are able to significantly influence AI adoption are Facilitating Conditions (FC) (H4) and Habit (H) (H6), with the remainder being statistically insignificant. As for the relationship between Auditor Adoption of AI (AAI) and Sustainable Audit Quality (SAQ) (H8), the test shows that auditors AI adoption possesses a statistically significant effect on sustainable audit quality. The fourth hypothesis has a *p* value of 0.000 and t statistic value of 4.328; the sixth hypothesis resulted in a p value of 0.000 and t statistic of 4.817; and the eighth hypothesis resulted in a *p* value of 0.000 and t statistic of 18.507. As for the rest of the hypotheses, the first hypothesis resulted in a *p* value of 0.629 and t statistic value of 0.484; the second hypothesis resulted in a *p* value of 0.333 and t statistic value of 0.969 ; the third hypotheses resulted in a *p* value of 0.533 and t statistic value of 0.623; the fifth hypothesis resulted in a *p* value of 0.708 and t statistic value of 0.374; and the seventh hypothesis resulted in a *p* value of 0.215 and t statistic value of 1.239.

Based on this result, the test shows that the hypothesized relationship between the independent and dependent variables are mostly insignificant in regard to auditors' AI adoption, with the exception of Facilitating Conditions and Habit. It should also be noted that based on the test, auditors' AI adoption itself has a significant direct influence towards sustainable audit quality.

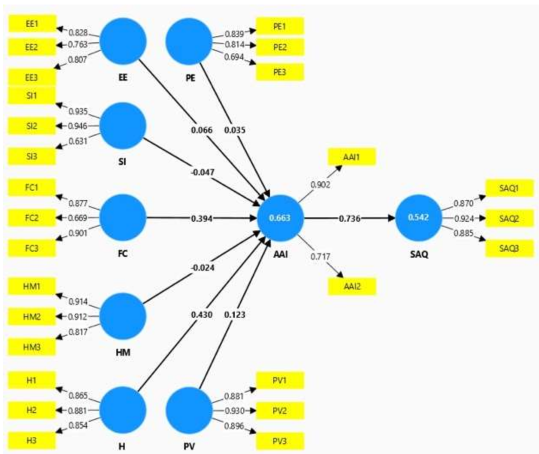

Figure. 2: Research Path Coefficient

4.6 Discussion

The outcome of the hypothesis testing shows that only a limited number of variables significantly impact auditors' adoption of AI (AAI). Specifically, Facilitating Conditions (FC) and Habit (H) have a positive and statistically significant effect on AAI, as evidenced by their high t-statistics and *p* values well below the 0.05 threshold. This suggests that auditors are more likely to adopt AI when they have the necessary resources and support infrastructure, such as dedicated AI programs for audit, reliable IT support for AI issues (FC), and when AI use becomes a habitual part of their workflow (H). These findings align with Samiolo's 2023 study, which suggests that habit, built through routine interactions with AI, plays a crucial role in influencing how comfortably and effectively auditors can incorporate AI into their professional practices [23]. Additionally, Leocádio's 2024 study also supports these findings, highlighting the importance of organizational preparedness for successful AI integration in audit procedures, which includes easily available technology and a supportive infrastructure [42]. A supportive infrastructure, including AI-compatible tools and platforms, as well as managers who provide a supportive environment enable auditors to overcome potential resistance to new technologies [42]. The study further emphasizes that AAI has a significant impact on Sustainable Audit Quality (SAQ), with a very strong t-statistic of 18.507 and a *p* value of 0.000. This result indicates that AI adoption could meaningfully enhance audit quality by improving the accuracy, efficiency, and sustainability of audits. This is in line with the results of Hasan's 2022 study, which similarly emphasizes AI's ability to improve efficiency, reduce errors, and free auditors from repetitive tasks, allowing them to focus on more complex, value-added work. This relationship reinforces the idea that AI adoption can be a key driver of improved audit quality in the long term [6].

In contrast, other variables—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Hedonic Motivation (HM), and Price Value (PV)—do not show significant relationships with AAI. This indicates that perceived performance improvements, required effort, social influence, enjoyment, and cost considerations are not substantial factors driving AI adoption among auditors in this study.

Effort Expectancy (EE) does not significantly affect AAI likely because auditors perceive AI learning as a high-effort activity, which they may view to be too time consuming. This is especially true for accounting firms during peak seasons, where time scarcity becomes an incredibly prevalent issue with which auditors have to contend with. Studies conducted by Rehman also suggest that when professionals are already under substantial stress or workload, they may resist adopting new, effort-intensive technologies [43]. In contrast, however, Atta's study [44] shows that EE is a significant factor in the inclusion of Computer Assisted Auditing Techniques (CAATs) by auditors in their work. This is most likely due to the fact that AI is a relatively newer technology than CAATs, and auditors remain skeptical about how AI implementation may benefit auditing in the long-term in comparison with CAATs. It should be emphasized that just like AI, when CAATs were a relatively new concept, auditors were also dubious in it. They believed that the learning curve and time commitment required to successfully use CAATs

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

were too steep. However, as user-friendly interfaces and extensive training programs grow, entry barriers to CAATs continue to fall to the point where their use is now routine in most accounting companies. This shows the necessity for accounting firms to develop training programs and develop easier to use user interface for AI programs in order to reduce the entry barriers of AI in audit.

Hedonic Motivation (HM) is also insignificant, likely due to the fact that auditors view AI as a work tool rather than a source of personal enjoyment or lifestyle enhancement. For instance, in consumer contexts, hedonic motivation has a stronger influence on adoption for technologies like online shopping, where personal enjoyment plays a role. However, in the professional context of auditing, the purpose of AI is to assist with tasks rather than provide pleasure, which may account for the lack of a significant relationship. These findings align with the preliminary research conducted by Tseng [32], which studied teachers' adoption of technology in educational context using UTAUT 2 as a theoretical foundation. His study showed that HM had an insignificant influence towards teachers' technological adoption, due to the similarity of teaching with a utilitarian task, instead of a hedonic task. This reason is likely also why HM is insignificant in the context of auditors' AI adoption, who view their work as a strictly utilitarian task, not a hedonic task from which they can derive pleasure from.

Performance Expectancy (PE) does not significantly influence AAI either, which may indicate that auditors are not fully aware of AI's potential to enhance their work performance. Including recommendations in the conclusion for accounting firms to raise awareness about AI's benefits could help bridge this gap. These findings align with the preliminary research conducted by Hasan in 2022, who stated that if auditors passively accept AI without understanding how it works or what it can do, it will certainly affect decisions about applying AI to audits [6].

Price Value (PV) also lacks significance, suggesting that auditors still perceive AI as costly, particularly due to the expenses associated with high-capability AI tools, such as advanced, specialized audit software. Many of these tools require substantial upfront investments and ongoing maintenance fees, which may deter adoption if auditors feel the cost does not justify the perceived benefits. These findings align with preliminary research by Law, indicating that AI, while improving efficiency, does not reduce audit fees [45]. Audit partners report that, even with automation, firms still need personnel to operate, analyze, and document the outputs generated by these tools. One partner explains, "These tools may save some labor costs, but they are very costly to invest in.".

Social Influence (SI) is found to be insignificant, indicating that auditor AI adoption is generally independent of peer or social influence. Unlike consumer tech adoption, where peer recommendations can play a significant role, auditors seem to rely on their own judgment rather than on others' usage when deciding to adopt AI in their work. These findings do not align with the preliminary research conducted by Ferri, who showed that SI has a positive effect on risk professionals' intention to implement AI in their work [18].

5. CONCLUSION AND SUGGESTION

This study provides important insights into the challenges and opportunities related to the adoption of AI in the auditing profession. One of the key findings is the widespread lack of awareness and understanding among auditors regarding the potential benefits of AI. While AI offers substantial advantages in automating repetitive tasks, improving decision-making, and enhancing audit quality, many auditors remain hesitant to adopt these technologies. The perception that AI is complex and difficult to learn is prevalent, hindering the willingness to explore AI's full capabilities.

For public accounting firms and partners, these findings highlight the need for proactive efforts to raise AI awareness and encourage adoption among auditors. Firms should invest in training programs that emphasize AI's practical benefits and ease of use, addressing the misconception that AI is difficult to learn. AI tools are becoming more user-friendly, and emphasizing their simplicity can reduce adoption barriers. Additionally, firms must clarify that the long-term value of AI tools, such as improved efficiency and reduced errors, far outweighs their cost. Providing auditors with hands-on experience through pilot programs or free trials will help build confidence. Firm leadership should actively support AI adoption, creating a culture of innovation and demonstrating the value of AI through their own practices, ultimately fostering an environment where auditors are more inclined to embrace new technologies.

Based on these findings, suggestions for future research include expanding the range of factors considered in technology adoption studies. Future researchers should consider incorporating additional psychological and demographic factors, as this study's results indicate there may be other external parameters that could directly or indirectly influence the dependent variable. For instance, theories like the Technology-Organization-Environment (TOE) framework or the DeLone and McLean IS Success Model could provide a broader perspective, potentially offering insights into other dimensions impacting auditor adoption of AI. Additionally, future studies could investigate how significant portions of variance from other fields might better represent influences on behavioral intentions toward AI adoption.

6. ACKNOWLEDGMENT

Our deepest gratitude to the Research Technology and Transfer Office of Bina Nusantara University for funding the publication of this research. Contributors of the paper: conceptualization: Handoko; methodology: Handoko; software: Handoko; validation: Tritama; Mahaprajna; formal analysis: Handoko; investigation: Tritama, Mahaprajna; resources: Tritama, Mahaprajna; data curation: Handoko; writing-original draft: Tritama, Mahaprajna; writing-review and editing: Handoko; visualization: Tritama, Mahaprajna; supervision: Handoko; project administration: Handoko; funding acquisition: Tritama, Mahaprajna

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